

# 16: Continuous Joint Distributions

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Lisa Yan

May 11, 2020

# Quick slide reference

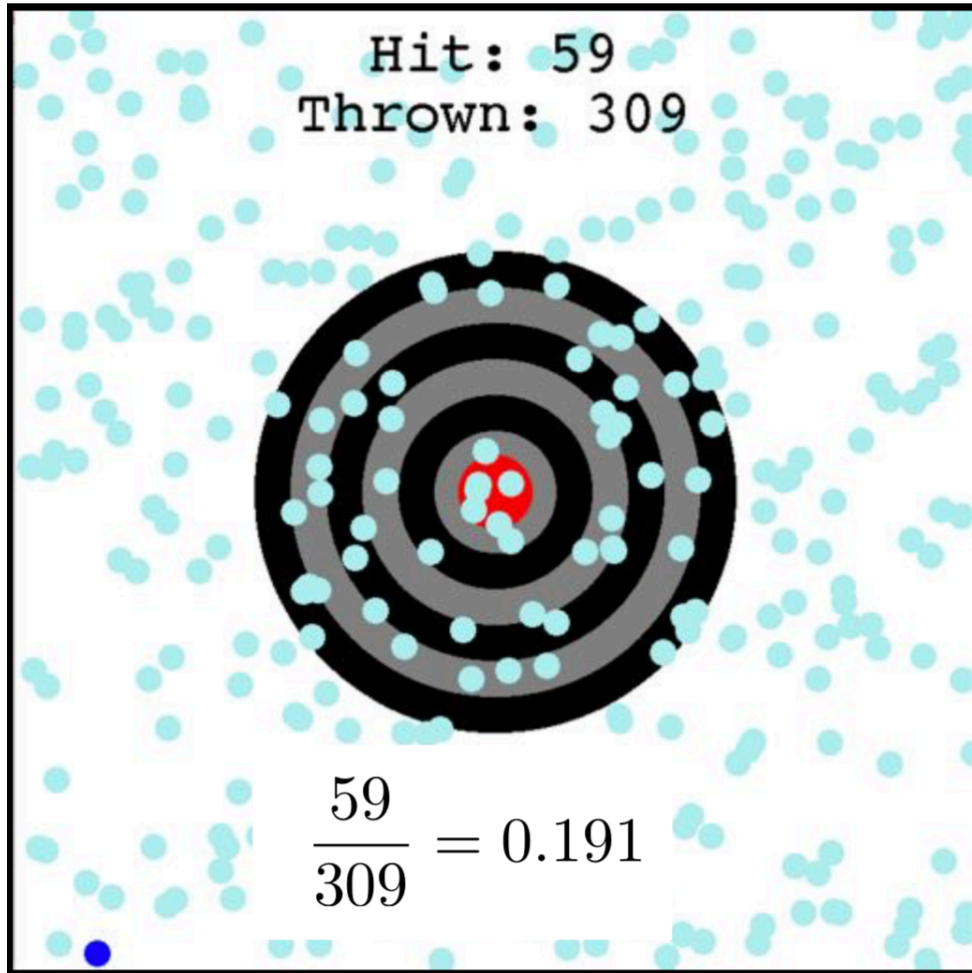
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3	Continuous joint distributions	16a_cont_joint
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# Continuous joint distributions

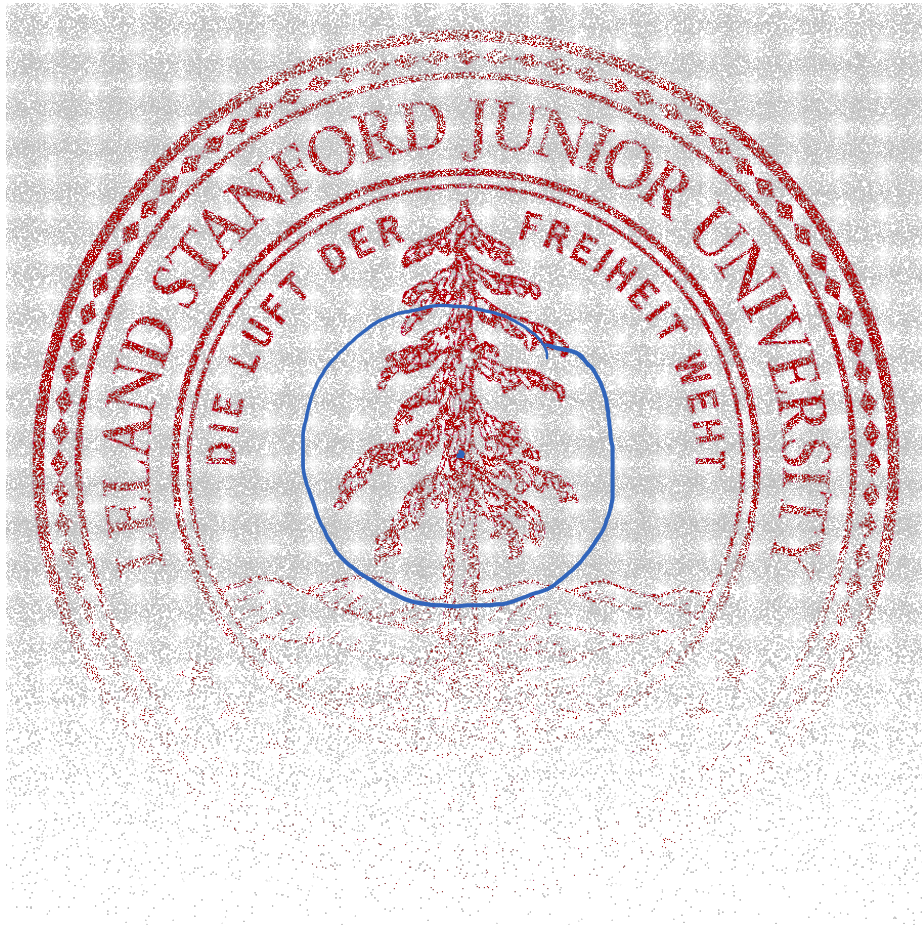
# Remember target?

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Good times...

# CS109 logo with darts



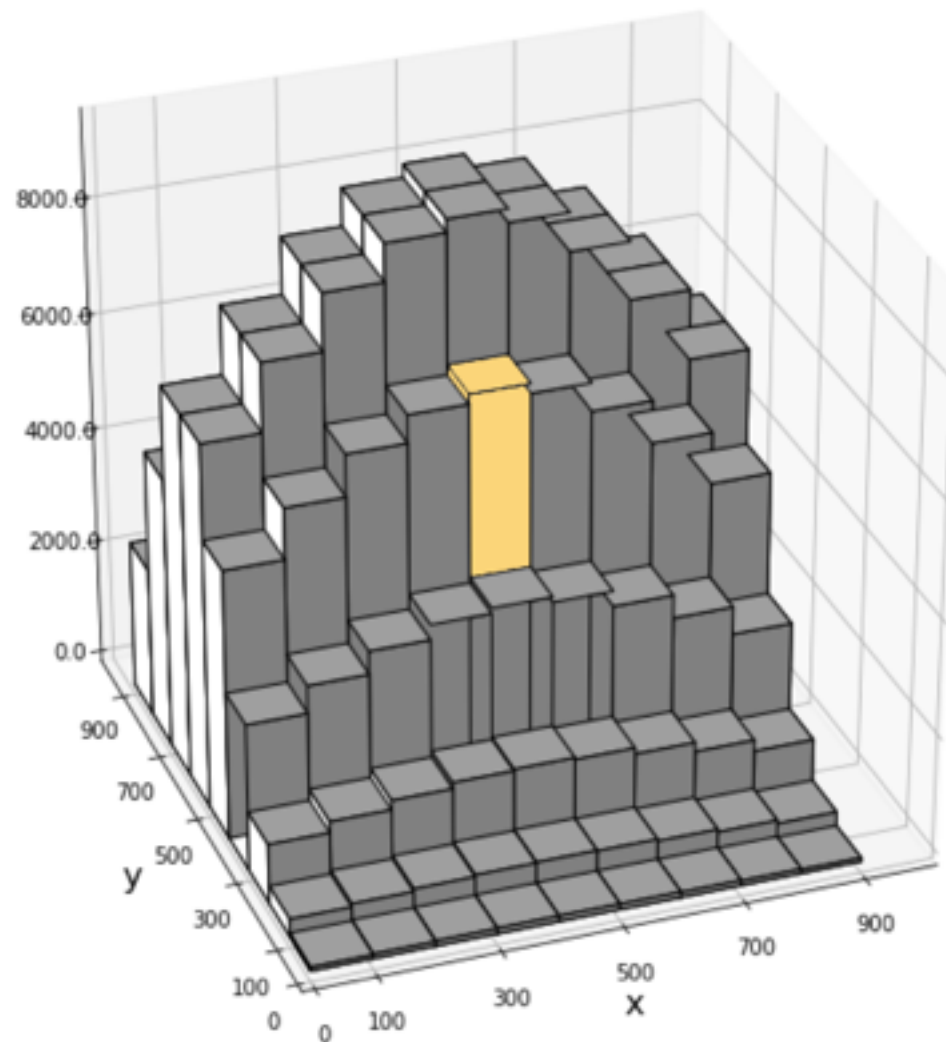
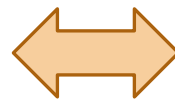
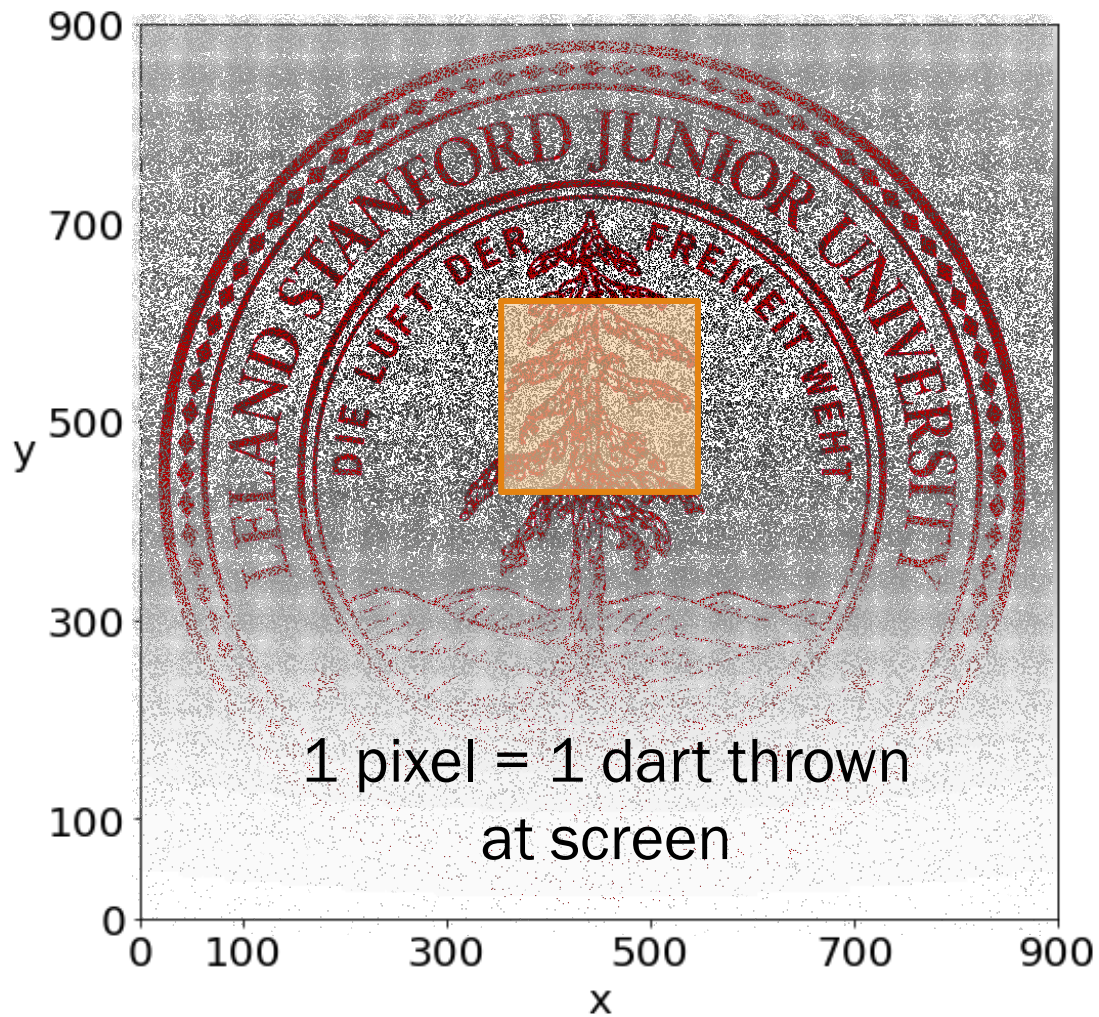
The CS109 logo was created by throwing 500,000 darts according to a joint distribution.

If we throw another dart according to the same distribution, what is  $P(\text{dart hits within } r \text{ pixels of center})$ ?

Quick check: What is the probability that a dart hits at  $(456.2344132343, 532.1865739012)$ ?

# CS109 logo with darts

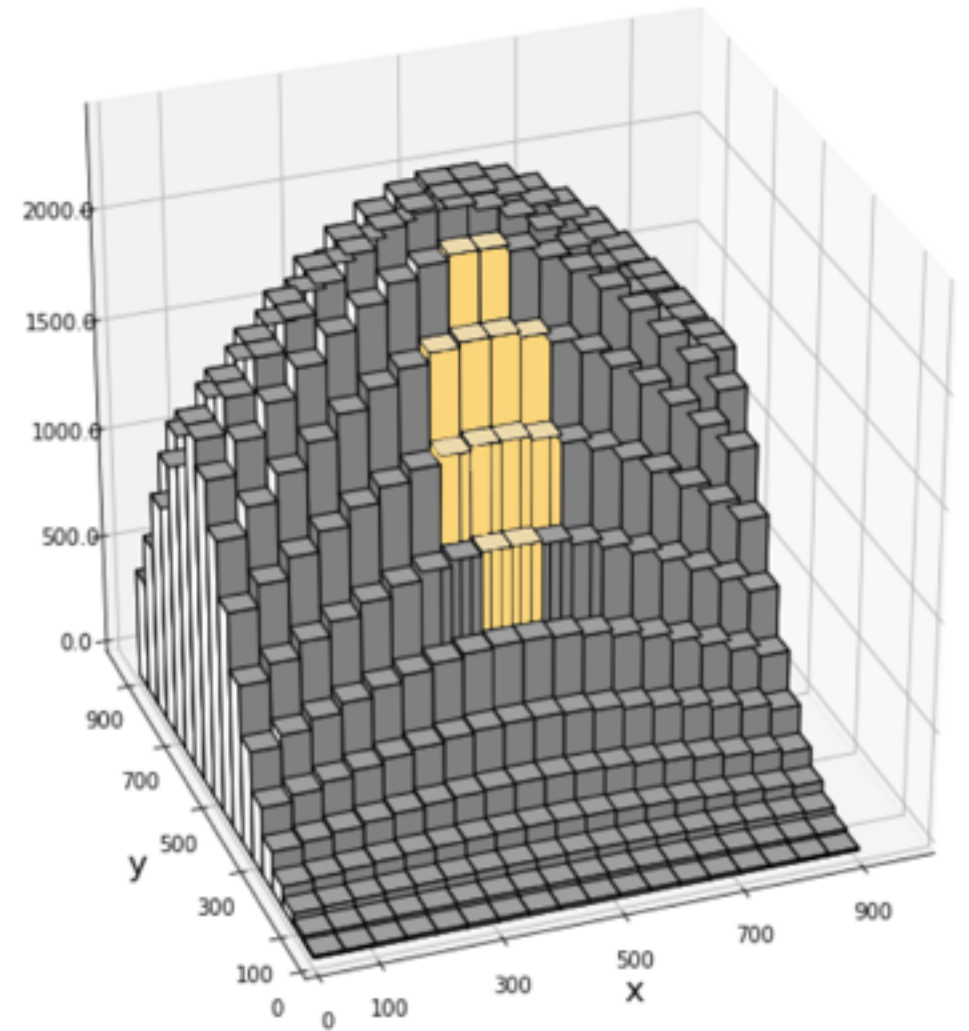
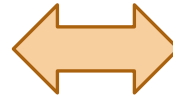
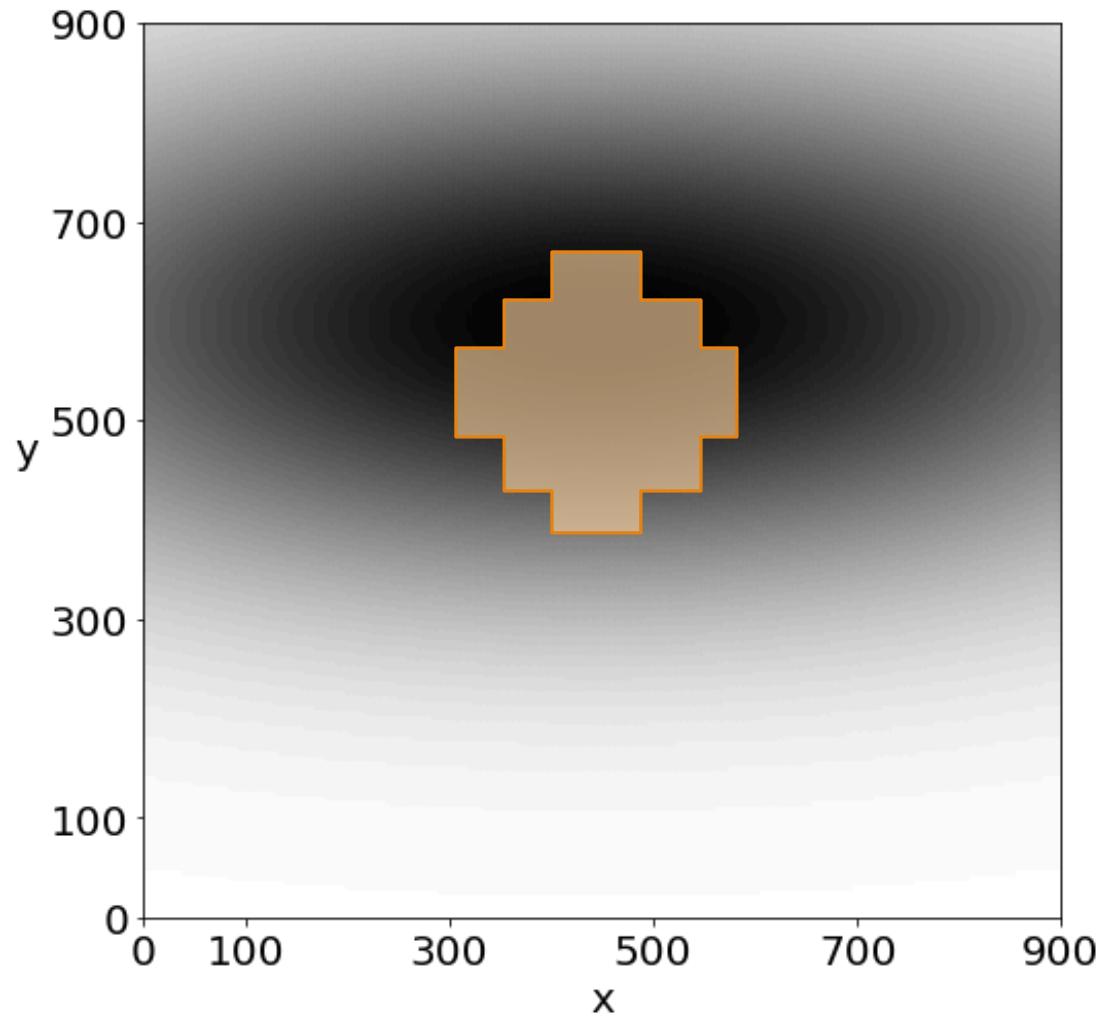
$P(\text{dart hits within } r \text{ pixels of center})?$



Possible dart counts (in 100x100 boxes)

# CS109 logo with darts

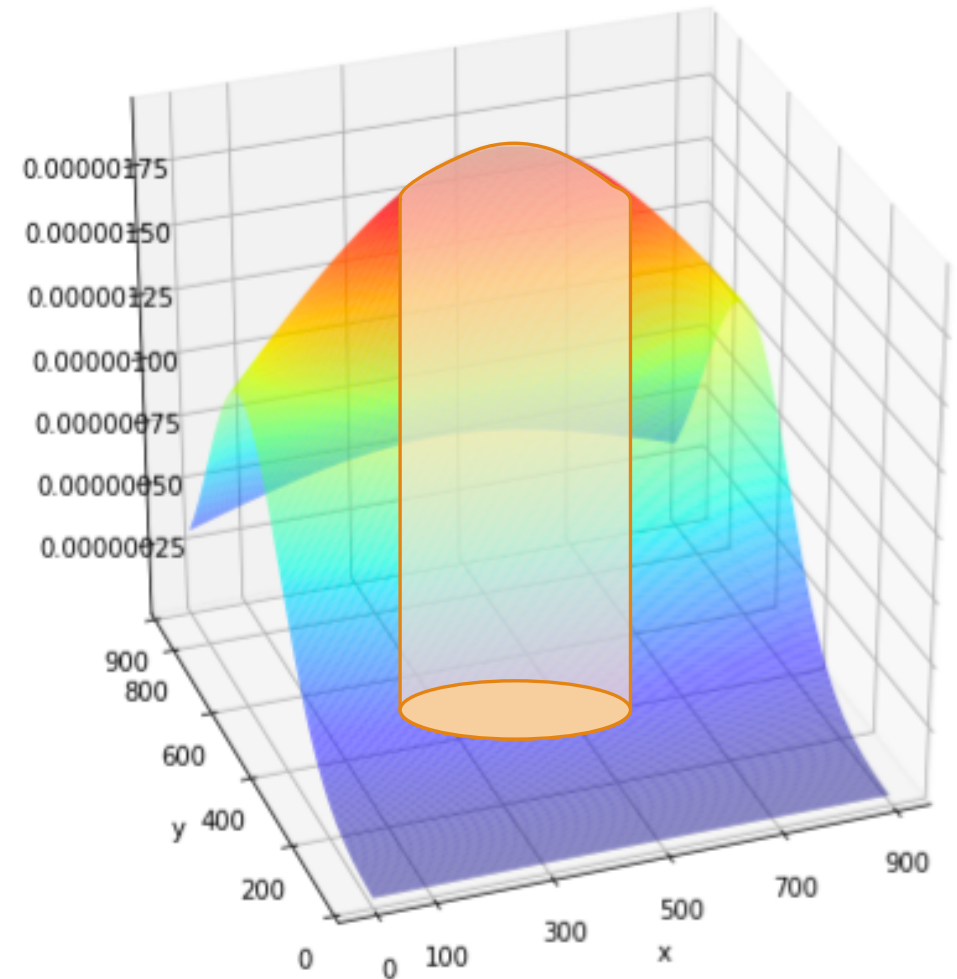
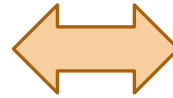
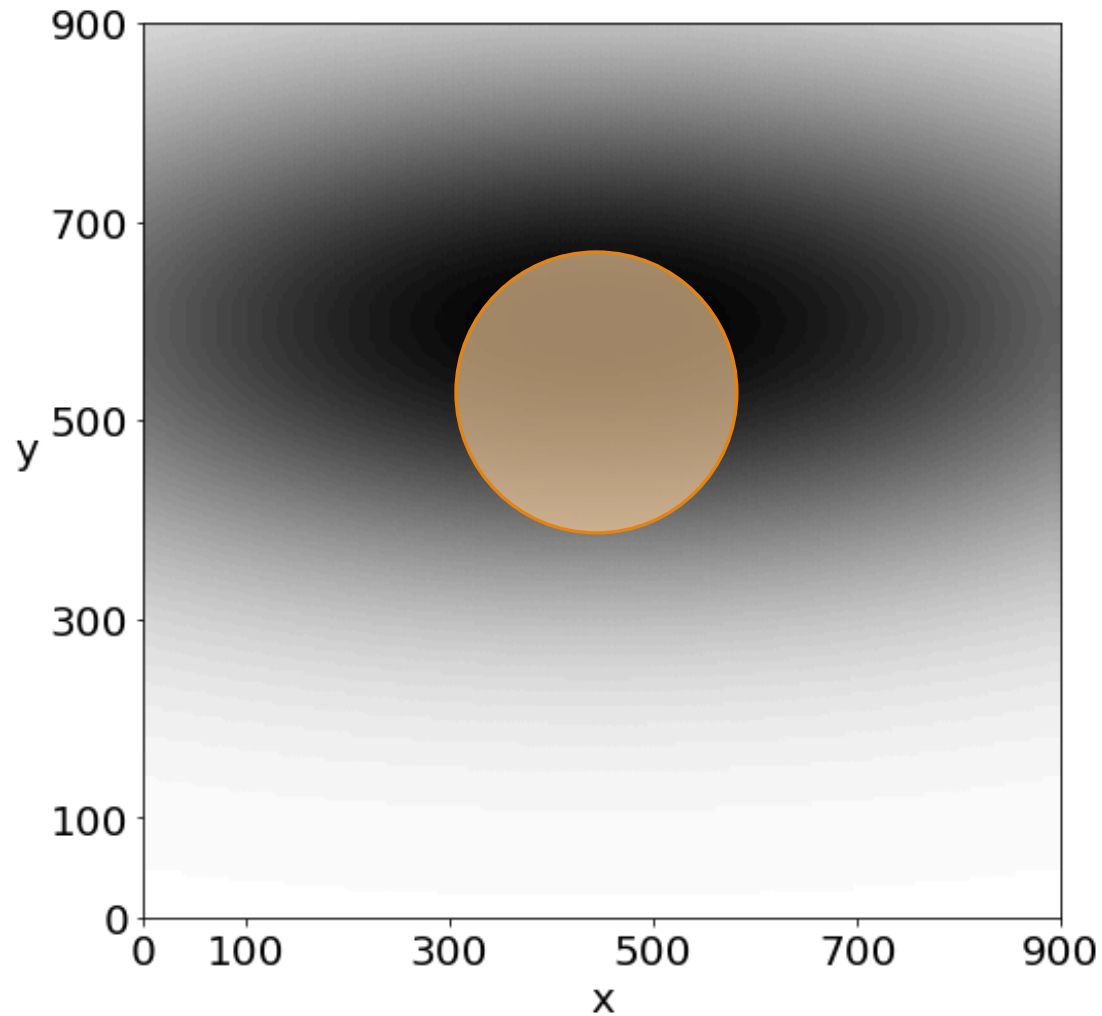
$P(\text{dart hits within } r \text{ pixels of center})?$



Possible dart counts (in 50x50 boxes)

# CS109 logo with darts

$P(\text{dart hits within } r \text{ pixels of center})?$



Possible dart counts  
(in infinitesimally small boxes) iversity 8



# Continuous joint probability density functions

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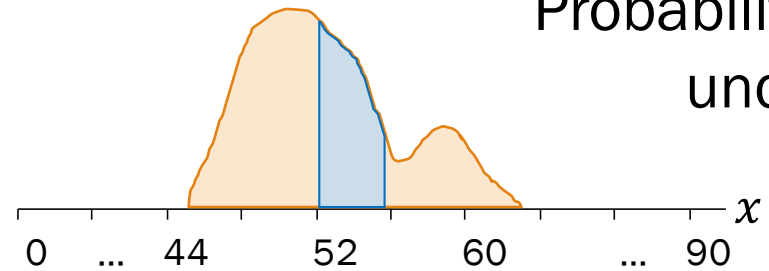
If two random variables  $X$  and  $Y$  are jointly continuous, then there exists a **joint probability density function**  $f_{X,Y}$  defined over  $-\infty < x, y < \infty$  such that:

$$P(a_1 \leq X \leq a_2, b_1 \leq Y \leq b_2) = \int_{a_1}^{a_2} \int_{b_1}^{b_2} f_{X,Y}(x, y) dy dx$$

# From one continuous RV to jointly continuous RVs

## Single continuous RV $X$

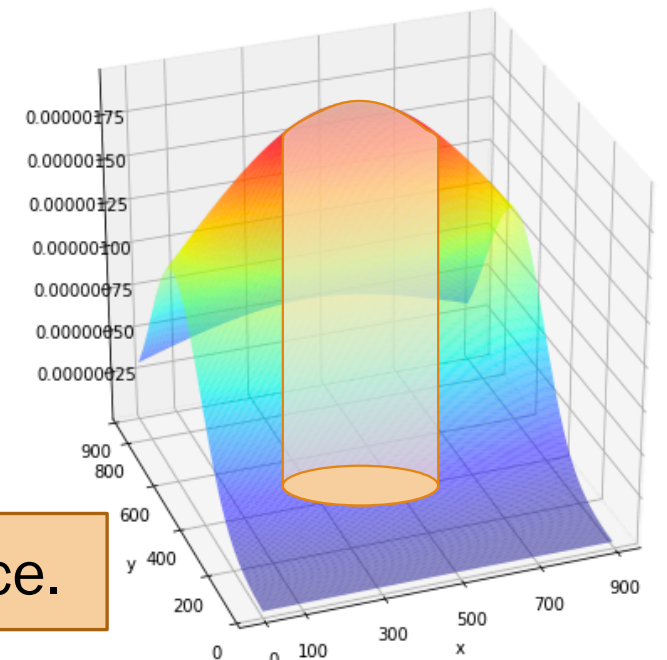
- PDF  $f_X$  such that  $\int_{-\infty}^{\infty} f_X(x) dx = 1$
- Integrate to get probabilities



Probability = **area**  
under curve

## Jointly continuous RVs $X$ and $Y$

- PDF  $f_{X,Y}$  such that  $\int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f_{X,Y}(x,y) dy dx = 1$
- Double integrate to get probabilities



Probability for jointly continuous RVs is **volume** under a surface.

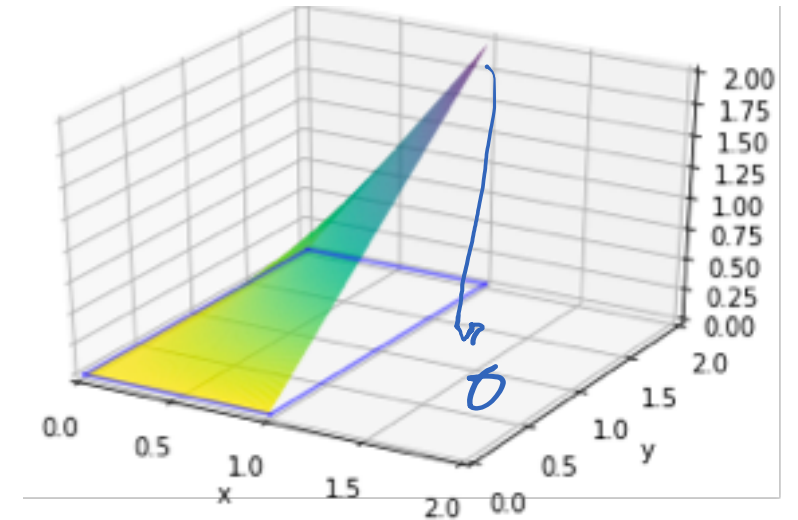
# Double integrals without tears

Let  $X$  and  $Y$  be two continuous random variables.

- Support:  $0 \leq X \leq 1$ ,  $0 \leq Y \leq 2$ .

Is  $g(x, y) = xy$  a valid joint PDF over  $X$  and  $Y$ ?

Write down the definite double integral that must integrate to 1:



# Double integrals without tears

Let  $X$  and  $Y$  be two continuous random variables.

- Support:  $0 \leq X \leq 1$ ,  $0 \leq Y \leq 2$ .

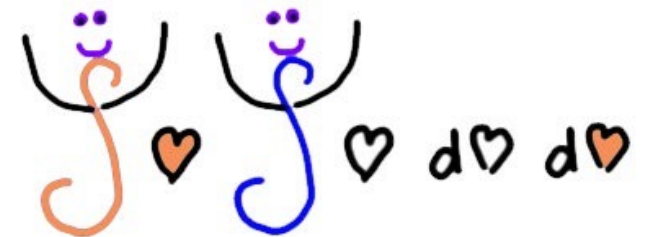
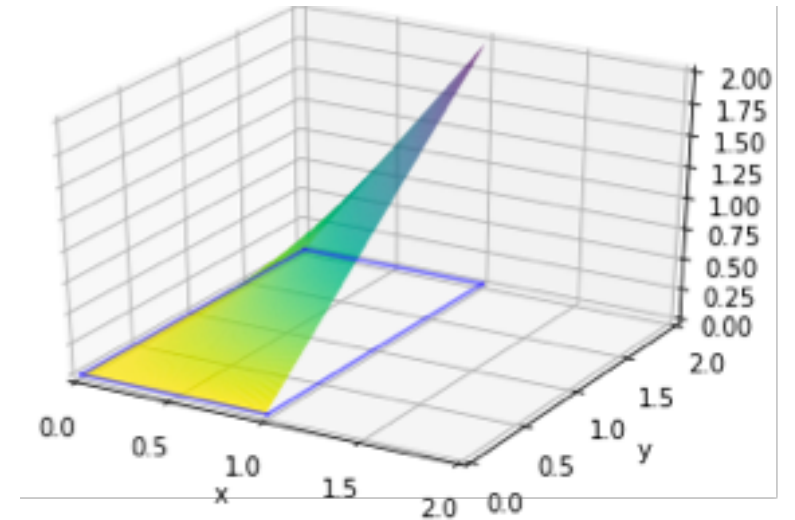
Is  $g(x, y) = xy$  a valid joint PDF over  $X$  and  $Y$ ?

Write down the definite double integral that must integrate to 1:

$$\int_{y=0}^2 \int_{x=0}^1 xy \, dx \, dy = 1 \quad \text{or} \quad \int_{x=0}^1 \int_{y=0}^2 xy \, dy \, dx = 1$$



(used in next slide)



# Double integrals without tears

Let  $X$  and  $Y$  be two continuous random variables.

- Support:  $0 \leq X \leq 1$ ,  $0 \leq Y \leq 2$ .

Is  $g(x, y) = xy$  a valid joint PDF over  $X$  and  $Y$ ?

0. Set up integral:

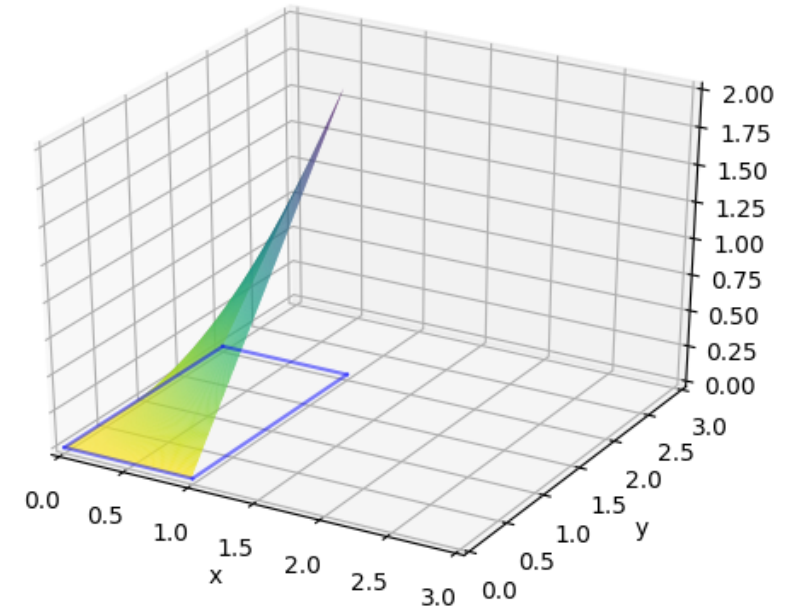
$$1 = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} g(x, y) dx dy = \int_{y=0}^2 \int_{x=0}^1 xy dx dy$$

1. Evaluate inside integral by treating  $y$  as a constant:

$$\int_{y=0}^2 \left( \int_{x=0}^1 xy dx \right) dy = \int_{y=0}^2 y \left( \int_{x=0}^1 x dx \right) dy = \int_{y=0}^2 y \left[ \frac{x^2}{2} \right]_0^1 dy = \int_{y=0}^2 y \frac{1}{2} dy$$

2. Evaluate remaining (single) integral:

$$\int_{y=0}^2 y \frac{1}{2} dy = \left[ \frac{y^2}{4} \right]_{y=0}^2 = 1 - 0 = 1$$

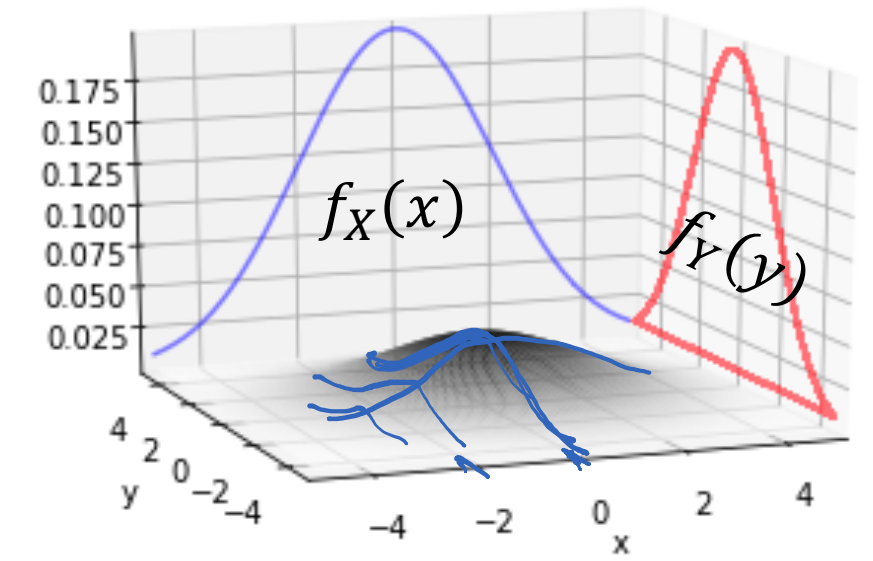


Yes,  $g(x, y)$  is a valid joint PDF because it integrates to 1.

# Marginal distributions

Suppose  $X$  and  $Y$  are continuous random variables with joint PDF:

$$\int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f_{X,Y}(x, y) dy dx = 1$$



The marginal density functions (**marginal PDFs**) are therefore:

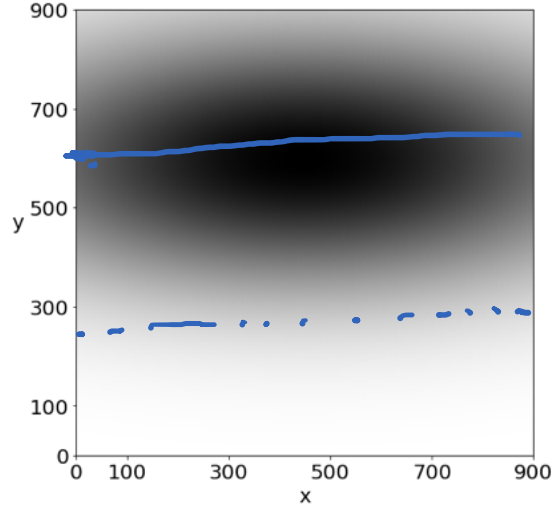
$$f_X(a) = \int_{-\infty}^{\infty} f_{X,Y}(a, y) dy$$

$$f_Y(b) = \int_{-\infty}^{\infty} f_{X,Y}(x, b) dx$$

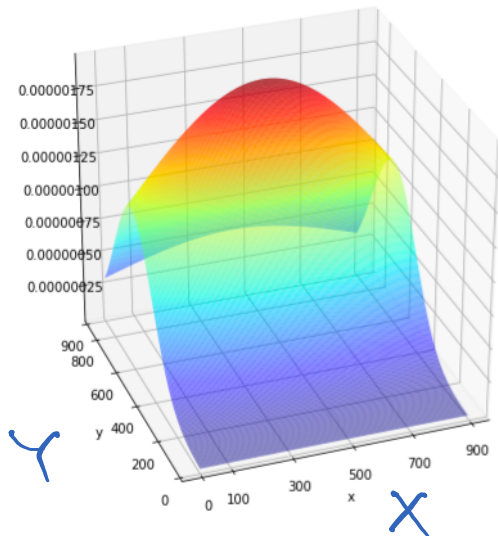
$$P_X(a) = \sum_y P_{X,Y}(a, y)$$

# Back to darts!

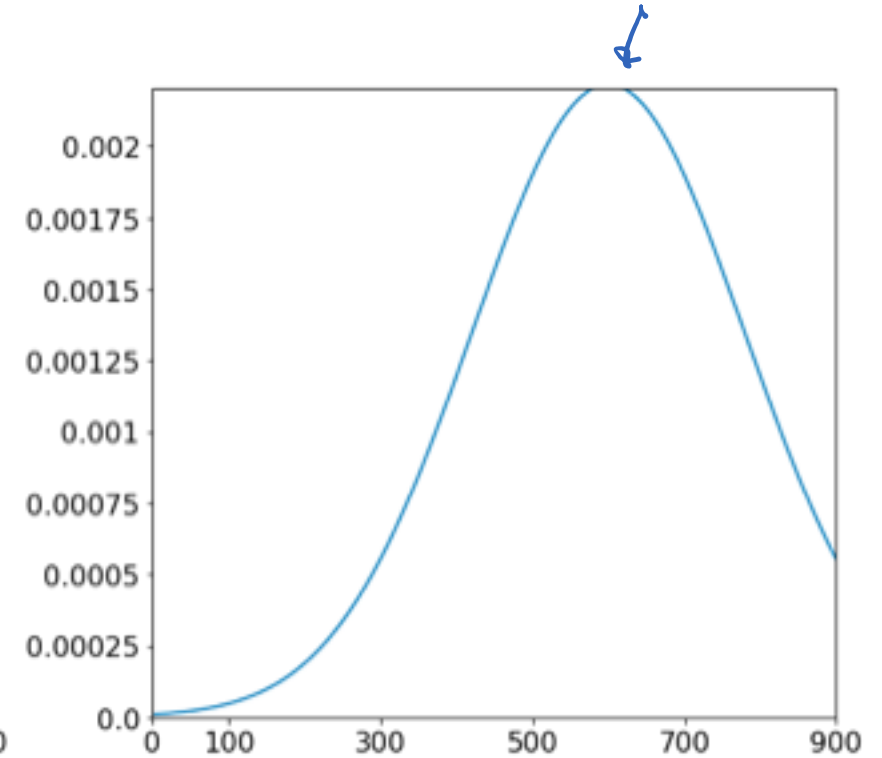
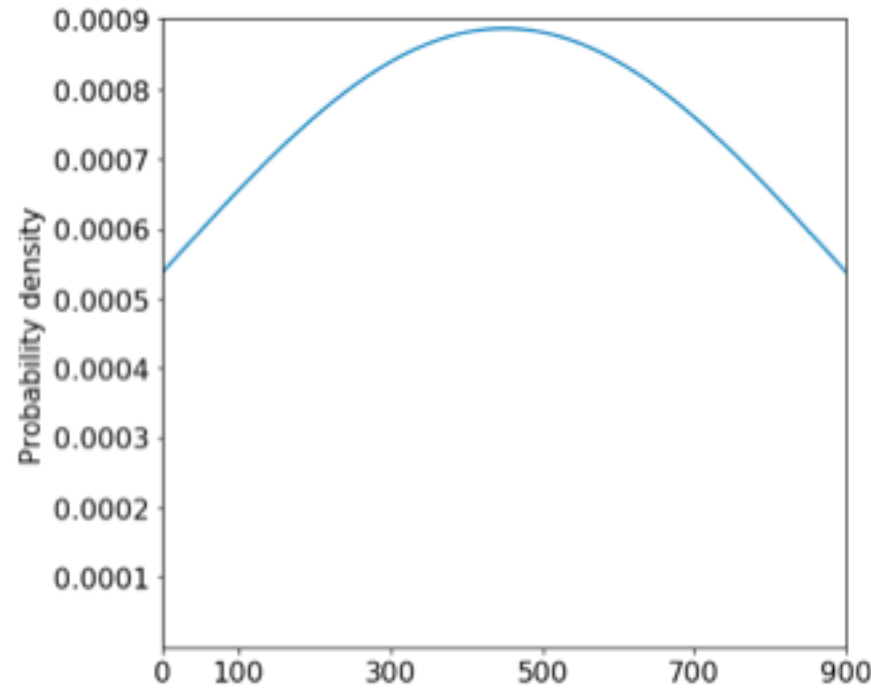
(top-down)



(side view)

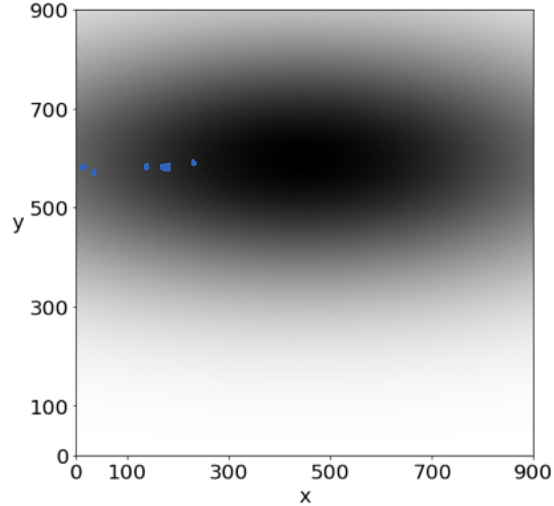


Match  $X$  and  $Y$  to their respective marginal PDFs:

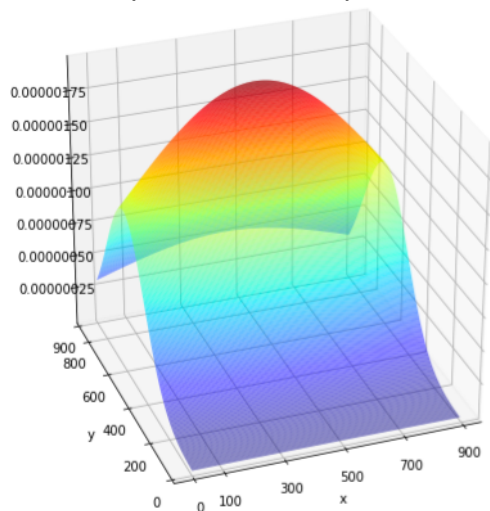


# Back to darts!

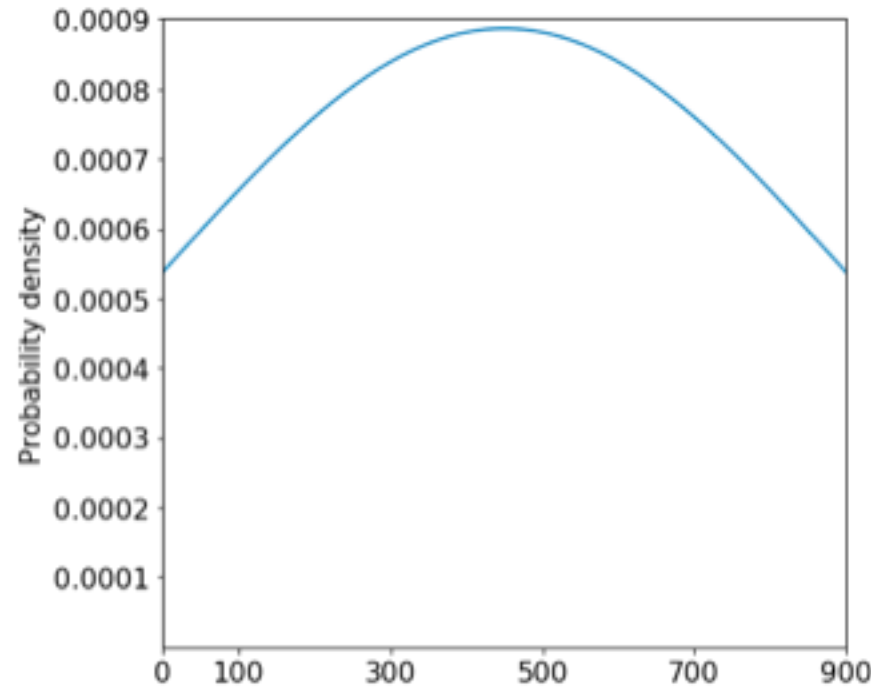
(top-down)



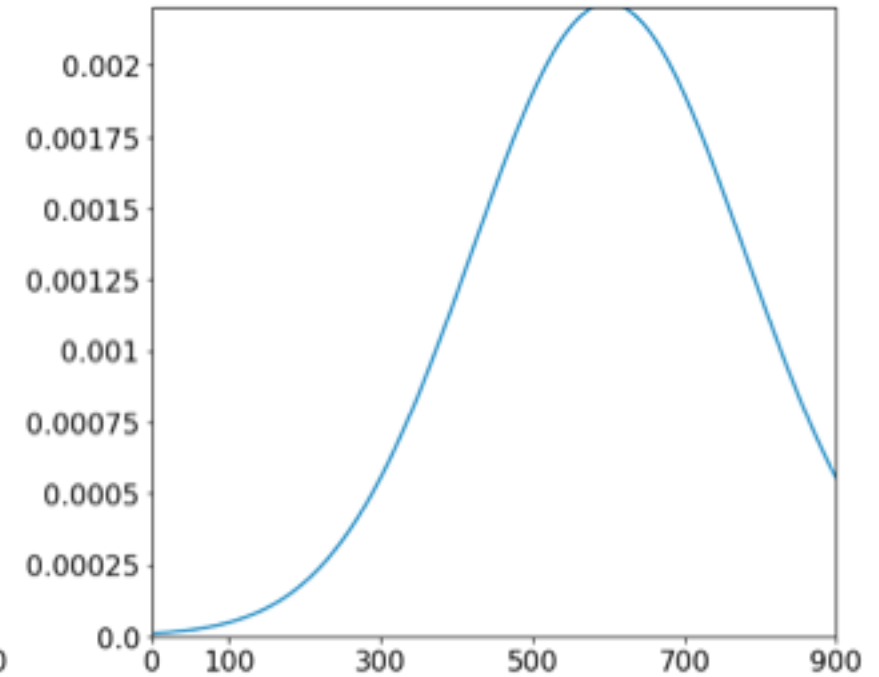
(side view)



Match  $X$  and  $Y$  to their respective marginal PDFs:



pixel x



pixel y



# Extra slides

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If you want more practice with double integrals,  
I've included two exercises at the end of this lecture.

# Joint CDFs

# An observation: Connecting CDF to PDF

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For a continuous random variable  $X$  with PDF  $f$ , the CDF (cumulative distribution function) is

$$F(a) = P(X \leq a) = \int_{-\infty}^a f(x) dx$$

The density  $f$  is therefore the derivative of the CDF,  $F$ :

$$f(a) = \frac{d}{da} F(a)$$

(Fundamental Theorem of Calculus)

# Joint cumulative distribution function

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For two random variables  $X$  and  $Y$ , there can be a **joint cumulative distribution function**  $F_{X,Y}$ :

$$F_{X,Y}(a, b) = P(X \leq a, Y \leq b)$$

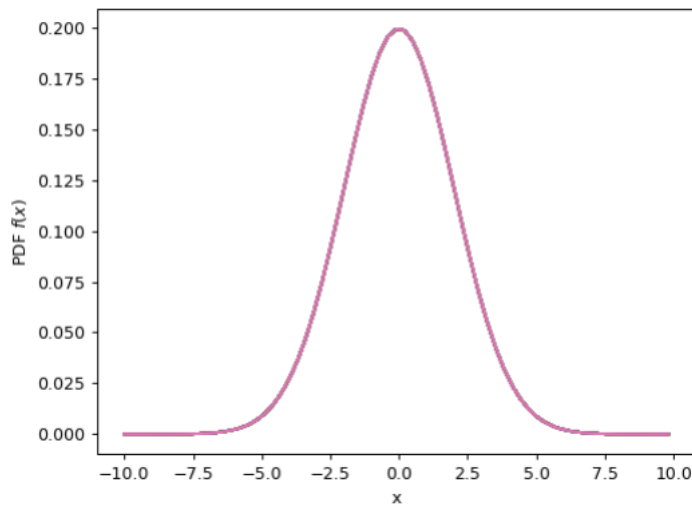
For discrete  $X$  and  $Y$ :

$$F_{X,Y}(a, b) = \sum_{x \leq a} \sum_{y \leq b} p_{X,Y}(x, y)$$

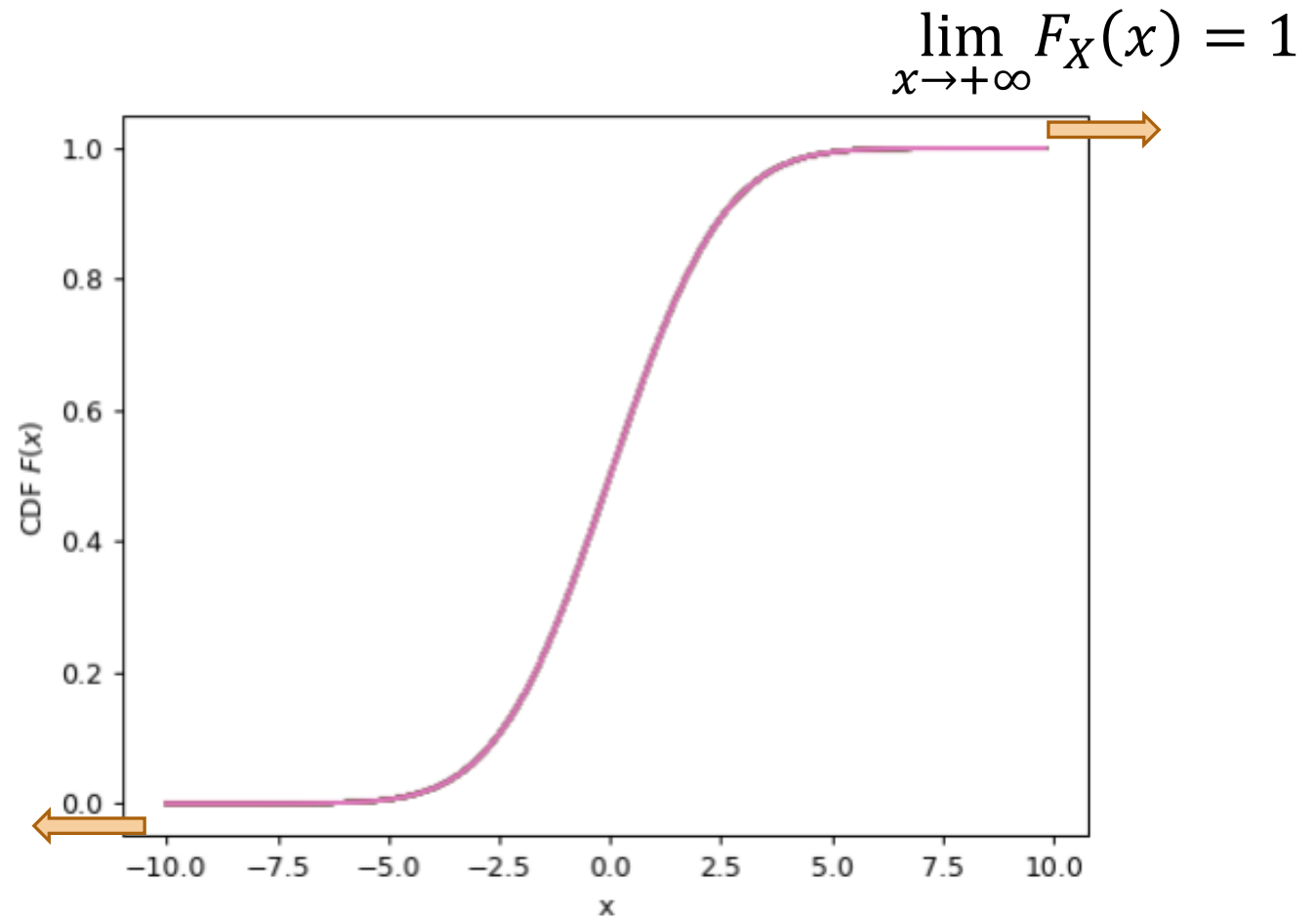
For continuous  $X$  and  $Y$ :

$$F_{X,Y}(a, b) = \int_{-\infty}^a \int_{-\infty}^b f_{X,Y}(x, y) dy dx$$
$$f_{X,Y}(a, b) = \frac{\partial^2}{\partial a \partial b} F_{X,Y}(a, b)$$

# Single variable CDF, graphically



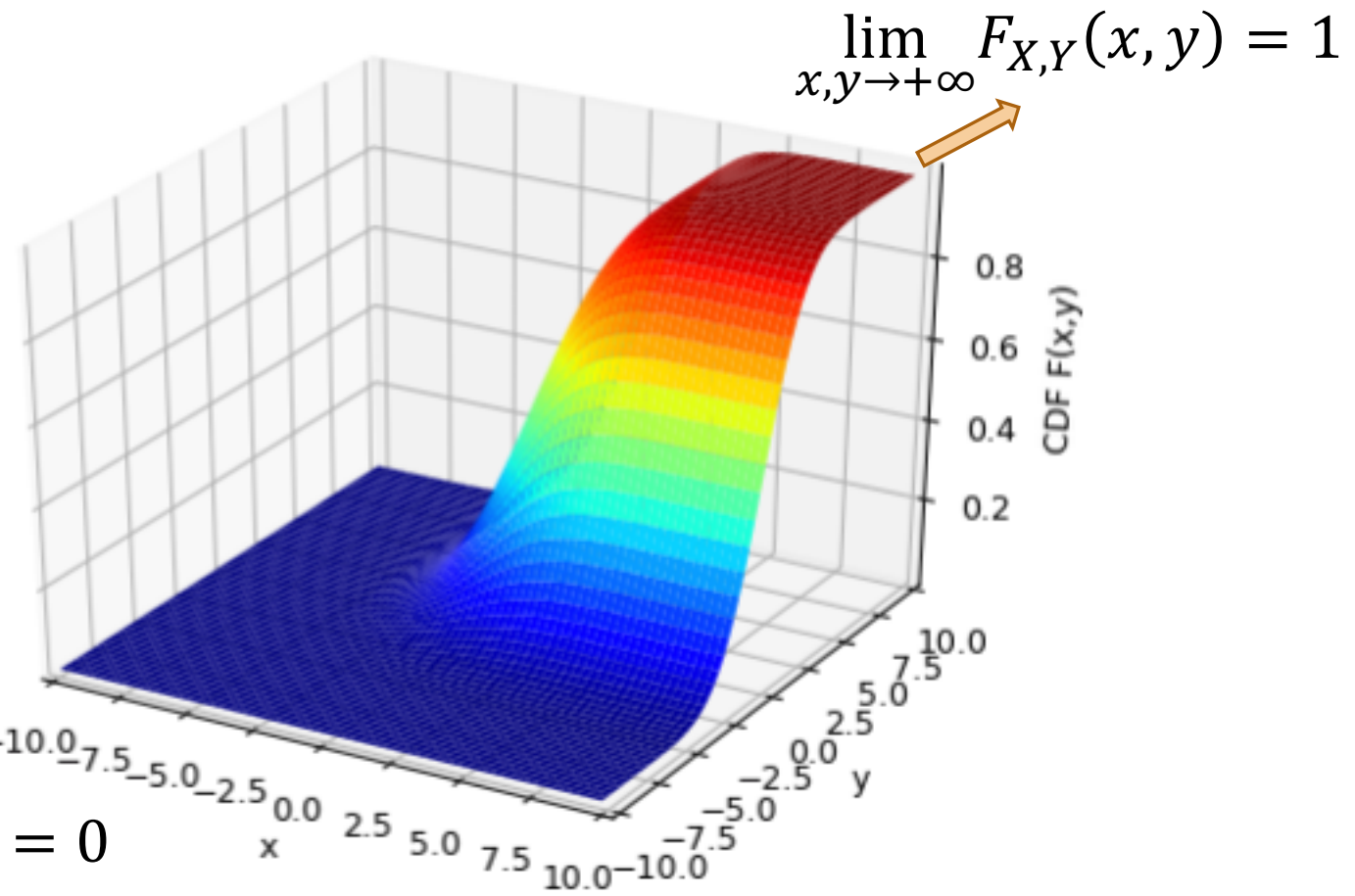
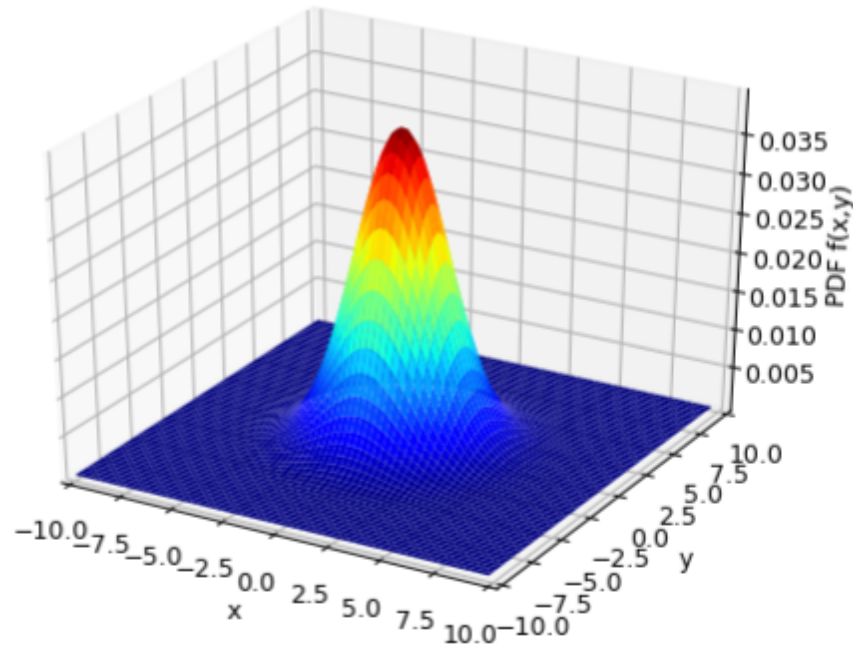
$$f_X(x)$$



$$\lim_{x \rightarrow -\infty} F_X(x) = 0$$

$$F_X(x) = P(X \leq x)$$

# Joint CDF, graphically



$$\lim_{x,y \rightarrow -\infty} F_{X,Y}(x,y) = 0$$

$$f_{X,Y}(x,y)$$

$$F_{X,Y}(x,y) = P(X \leq x, Y \leq y)$$

# Independent Continuous RVs

# Independent continuous RVs

Two continuous random variables  $X$  and  $Y$  are **independent** if:

$$P(X \leq x, Y \leq y) = P(X \leq x)P(Y \leq y)$$

$\forall x, y$

Equivalently:

$$\begin{aligned} F_{X,Y}(x, y) &= F_X(x)F_Y(y) \\ f_{X,Y}(x, y) &= f_X(x)f_Y(y) \end{aligned}$$

Proof of PDF:

$$\begin{aligned} f_{X,Y}(x, y) &= \frac{\partial^2}{\partial x \partial y} F_{X,Y}(x, y) = \frac{\partial^2}{\partial x \partial y} F_X(x)F_Y(y) \\ &= \frac{\partial}{\partial x} \frac{\partial}{\partial y} F_X(x)F_Y(y) = \frac{\partial}{\partial x} F_X(x) \frac{\partial}{\partial y} F_Y(y) \\ &= f_X(x)f_Y(y) \end{aligned}$$

$\forall x, y$



# Independent continuous RVs

---

Two continuous random variables  $X$  and  $Y$  are independent if:

$$P(X \leq x, Y \leq y) = P(X \leq x)P(Y \leq y)$$

Equivalently:

$$\begin{aligned}F_{X,Y}(x, y) &= F_X(x)F_Y(y) \\ f_{X,Y}(x, y) &= f_X(x)f_Y(y)\end{aligned}$$

More generally,  $X$  and  $Y$  are **independent** if joint density factors separately:

$$f_{X,Y}(x, y) = g(x)h(y), \text{ where } -\infty < x, y < \infty$$

# Pop quiz! (just kidding)

$$f_{X,Y}(x, y) = g(x)h(y),$$

where  $-\infty < x, y < \infty$

→ independent  
 $X$  and  $Y$

Are  $X$  and  $Y$  independent in the following cases?


1.  $f_{X,Y}(x, y) = 6e^{-3x}e^{-2y}$   
where  $0 < x, y < \infty$

2.  $f_{X,Y}(x, y) = 4xy$   
where  $0 < x, y < 1$

3.  $f_{X,Y}(x, y) = 24xy$   
where  $0 < x + y < 1$



# Pop quiz! (just kidding)

$f_{X,Y}(x, y) = g(x)h(y)$ ,  
where  $-\infty < x, y < \infty$   independent  
X and Y

Are  $X$  and  $Y$  independent in the following cases?

1.  $f_{X,Y}(x, y) = 6e^{-3x}e^{-2y}$   
where  $0 < x, y < \infty$

Separable functions:  $g(x) = 3e^{-3x}$   
 $h(y) = 2e^{-2y}$

2.  $f_{X,Y}(x, y) = 4xy$   
where  $0 < x, y < 1$

Separable functions:  $g(x) = 2x$   
 $h(y) = 2y$

$g(x) = 4x$   
 $h(y) = y$

3.  $f_{X,Y}(x, y) = 24xy$   
where  $0 < x + y < 1$

Cannot capture constraint on  $x + y$   
into factorization!

$\int_0^1 \int_0^{1-x} 4xy \, dy \, dx = 1 = \int_0^1 \underbrace{c \cdot 4x \, dx}_1 \cdot \int_0^1 \underbrace{\frac{1}{c} \cdot y \, dy}_1$

If you can factor densities over all of the support, you have independence.

# Bivariate Normal Distribution

# Bivariate Normal Distribution

$$X \sim \mathcal{N}(\mu, \sigma^2) \quad f(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(x-\mu)^2}{2\sigma^2}}$$

$X_1$  and  $X_2$  follow a bivariate normal distribution if their joint PDF  $f$  is

$$f(x_1, x_2) = \frac{1}{2\pi\sigma_1\sigma_2\sqrt{1-\rho^2}} e^{-\frac{1}{2(1-\rho^2)}\left(\frac{(x_1-\mu_1)^2}{\sigma_1^2} - \frac{2\rho(x_1-\mu_1)(x_2-\mu_2)}{\sigma_1\sigma_2} + \frac{(x_2-\mu_2)^2}{\sigma_2^2}\right)}$$

Can show that  $X_1 \sim \mathcal{N}(\mu_1, \sigma_1^2)$ ,  $X_2 \sim \mathcal{N}(\mu_2, \sigma_2^2)$  (Ross chapter 6, example 5d)

Often written as:

$$\mathbf{X} \sim \mathcal{N}(\boldsymbol{\mu}, \boldsymbol{\Sigma})$$

- Vector  $\mathbf{X} = (X_1, X_2)$

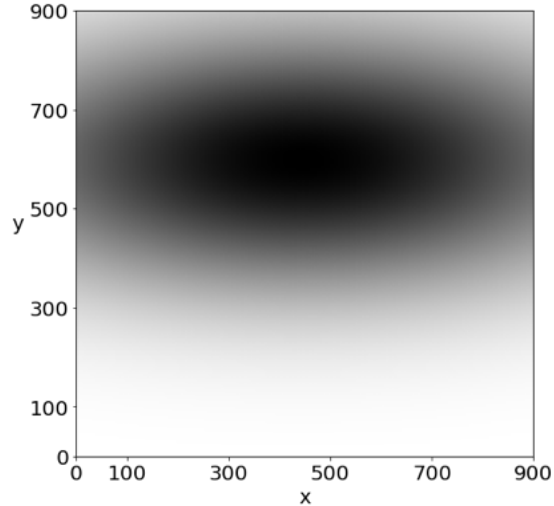
- Mean vector  $\boldsymbol{\mu} = (\mu_1, \mu_2)$ , Covariance matrix:  $\boldsymbol{\Sigma} = \begin{bmatrix} \sigma_1^2 & \rho\sigma_1\sigma_2 \\ \rho\sigma_1\sigma_2 & \sigma_2^2 \end{bmatrix} = \begin{bmatrix} \text{Cov}(X_1, X_1) & \text{Cov}(X_1, X_2) \\ \text{Cov}(X_2, X_1) & \text{Cov}(X_2, X_2) \end{bmatrix}$

Recall correlation:  $\rho = \frac{\text{Cov}(X_1, X_2)}{\sigma_1\sigma_2}$

We will focus on understanding the shape of a bivariate Normal RV.

# Back to darts

(top-down)



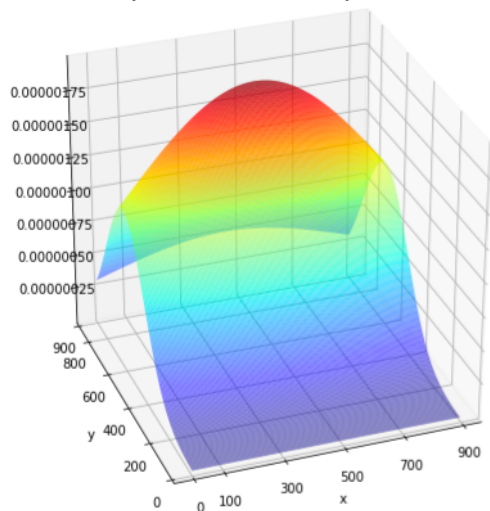
These darts were actually thrown according to a bivariate normal distribution:

$$(X, Y) \sim \mathcal{N}(\boldsymbol{\mu}, \boldsymbol{\Sigma})$$

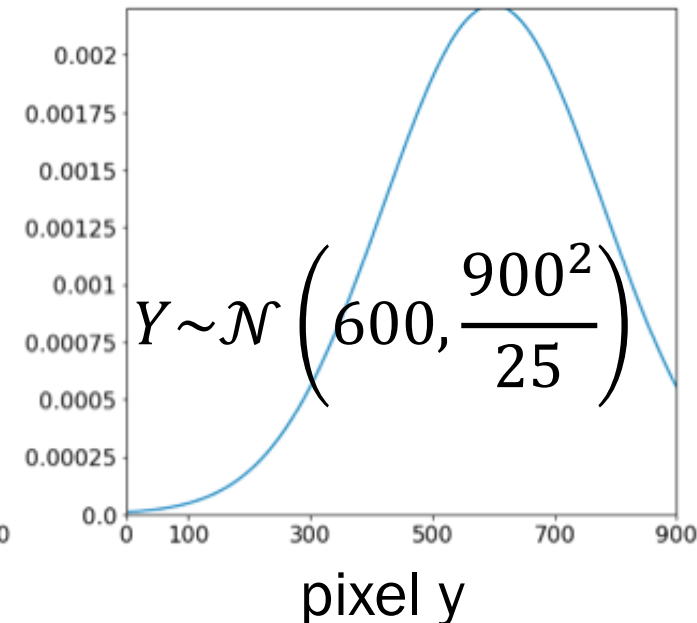
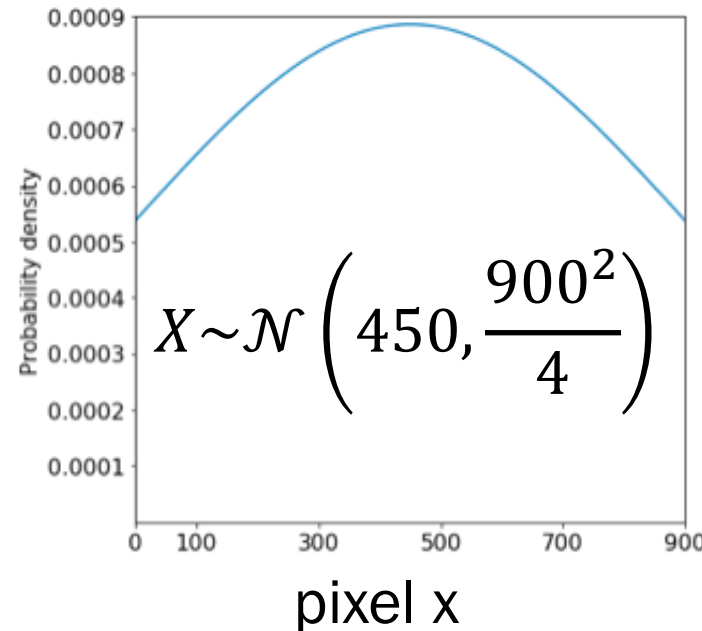
$$\boldsymbol{\mu} = (450, 600)$$

$$\boldsymbol{\Sigma} = \begin{bmatrix} 900^2/4 & 0 \\ 0 & 900^2/25 \end{bmatrix}$$

(side view)



Marginal  
PDFs:



# A diagonal covariance matrix

Let  $\mathbf{X} = (X_1, X_2)$  follow a bivariate normal distribution  $\mathbf{X} \sim \mathcal{N}(\boldsymbol{\mu}, \boldsymbol{\Sigma})$ , where

$$\boldsymbol{\mu} = (\mu_1, \mu_2),$$

$$\boldsymbol{\Sigma} = \begin{bmatrix} \sigma_1^2 & 0 \\ 0 & \sigma_2^2 \end{bmatrix}$$

$\leftarrow \text{Cov}(X_1, X_2) = \rho\sigma_1\sigma_2 = 0$

Are  $X_1$  and  $X_2$  independent?

$$f(x_1, x_2) = \frac{1}{2\pi\sigma_1\sigma_2\sqrt{1-\rho^2}} e^{-\frac{1}{2(1-\rho^2)}\left(\frac{(x_1-\mu_1)^2}{\sigma_1^2} - \frac{2\rho(x_1-\mu_1)(x_2-\mu_2)}{\sigma_1\sigma_2} + \frac{(x_2-\mu_2)^2}{\sigma_2^2}\right)}$$

$$= \frac{1}{2\pi\sigma_1\sigma_2} e^{-\frac{1}{2}\left(\frac{(x_1-\mu_1)^2}{\sigma_1^2} + \frac{(x_2-\mu_2)^2}{\sigma_2^2}\right)} \quad (\text{Note covariance: } \rho\sigma_1\sigma_2 = 0)$$

$$= \frac{1}{\sigma_1\sqrt{2\pi}} e^{-(x_1-\mu_1)^2/2\sigma_1^2} \frac{1}{\sigma_2\sqrt{2\pi}} e^{-(x_2-\mu_2)^2/2\sigma_2^2}$$

$X_1$  and  $X_2$  are independent with marginal distributions  $X_1 \sim \mathcal{N}(\mu_1, \sigma_1^2)$ ,  $X_2 \sim \mathcal{N}(\mu_2, \sigma_2^2)$

# 16: Continuous Joint Distributions (I) (live)

Lisa Yan  
May 11, 2020

$E[109]$



$X$  and  $Y$  are jointly continuous if they have a joint PDF:

$$f_{X,Y}(x, y) \text{ such that } \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f_{X,Y}(x, y) dy dx = 1$$

Most things we've learned about discrete joint distributions translate:

Marginal  
distributions

$$p_X(a) = \sum_y p_{X,Y}(a, y)$$

$$f_X(a) = \int_{-\infty}^{\infty} f_{X,Y}(a, y) dy$$

Independent RVs

$$p_{X,Y}(x, y) = p_X(x)p_Y(y)$$

$$f_{X,Y}(x, y) = f_X(x)f_Y(y)$$

Expectation  
(e.g., LOTUS)

$$E[g(X, Y)] = \sum_x \sum_y g(x, y)p_{X,Y}(x, y)$$

$$E[g(X, Y)] = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} g(x, y)f_{X,Y}(x, y) dy dx$$

...etc.

# Think

Slide 35 has a question to go over by yourself.

Post any clarifications here!

<https://us.edstem.org/courses/109/discussion/60584>

Think by yourself: 2 min



# Warmup exercise

---

$X$  and  $Y$  have the following joint PDF:

$$f_{X,Y}(x, y) = 3e^{-3x}$$

where  $0 < x < \infty, 1 < y < 2$

1. Are  $X$  and  $Y$  independent?
2. What is the marginal PDF of  $X$ ? Of  $Y$ ?
3. What is  $E[X + Y]$ ?



# Warmup exercise

$X$  and  $Y$  have the following joint PDF:

$$f_{X,Y}(x,y) = 3e^{-3x}$$

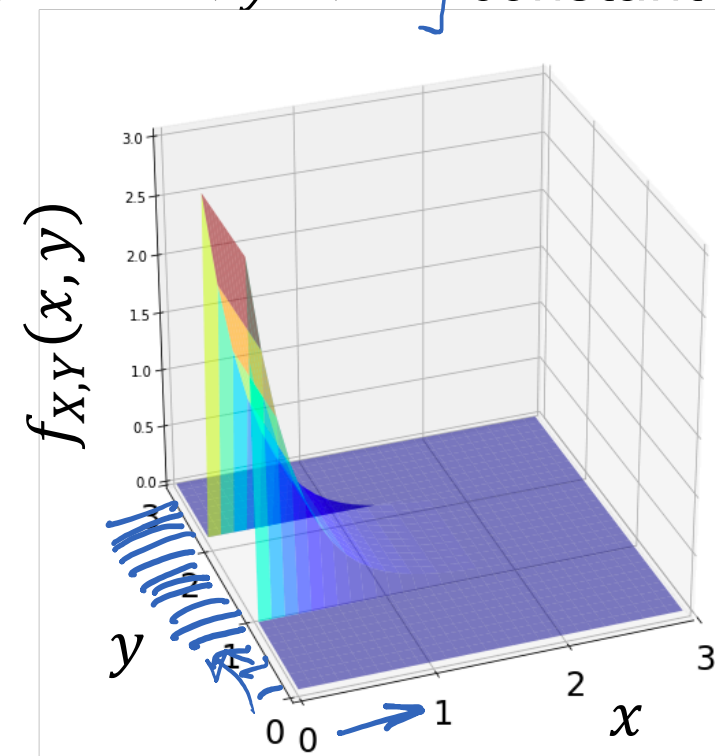
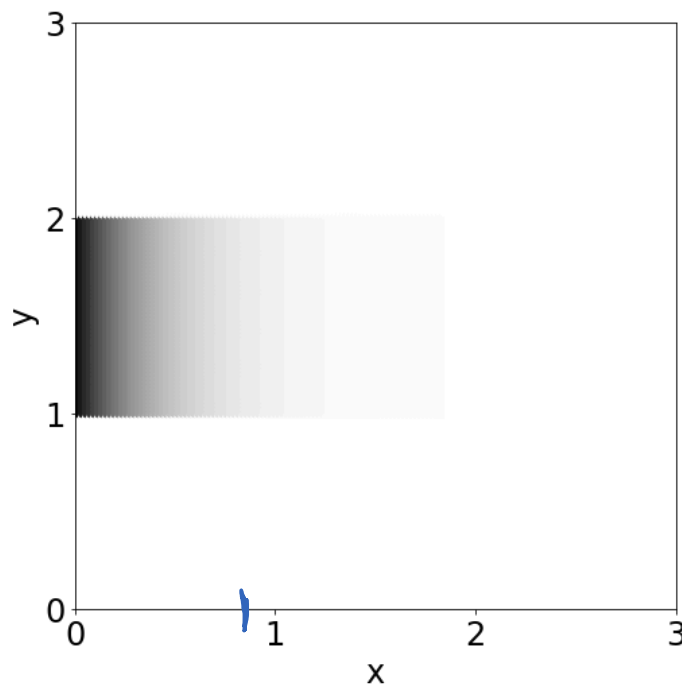
where  $0 < x < \infty, 1 < y < 2$

1. Are  $X$  and  $Y$  independent?

$$\left. \begin{aligned} g(x) &= 3Ce^{-3x}, 0 < x < \infty \\ h(y) &= 1/C, 1 < y < 2 \end{aligned} \right\} C \text{ is a constant}$$

2. What is the marginal PDF of  $X$ ? Of  $Y$ ?

3. What is  $E[X + Y]$ ?



# Warmup exercise

$X$  and  $Y$  have the following joint PDF:

$$f_{X,Y}(x,y) = 3e^{-3x}$$

where  $0 < x < \infty, 1 < y < 2$

1. Are  $X$  and  $Y$  independent?

$$g(x) = 3Ce^{-3x}, 0 < x < \infty \quad C \text{ is a constant}$$
$$h(y) = 1/C, \quad 1 < y < 2$$

2. What is the marginal PDF of  $X$ ? Of  $Y$ ?

$$x \geq 0 \quad f_X(x) = 3e^{-3x} \quad X \sim \text{Exp}(\lambda=3)$$
$$f_Y(y) = 1 \quad 1 < y < 2 \quad Y \sim \text{Unif}(a=1, b=2)$$

3. What is  $E[X + Y]$ ?

$$\text{Strategy 1: } \mathbb{E}[g(X,Y)] = \int_1^2 \int_0^{\infty} g(x,y) f_{X,Y}(x,y) dx dy$$

$$\text{Strategy 2: } \mathbb{E}[X+Y] = \mathbb{E}[X] + \mathbb{E}[Y]$$
$$1/3 + 3/2$$

# Breakout Rooms

Check out the question on the next slide (Slide 39). Post any clarifications here!

<https://us.edstem.org/courses/109/discussion/60584>

Breakout rooms: 4 min. Introduce yourself!



# The joy of meetings

Two people set up a meeting time. Each arrives independently at a time uniformly distributed between 12pm and 12:30pm.

Define  $X = \#$  minutes past 12pm that person 1 arrives.  $X \sim \text{Unif}(0, 30)$

$Y = \#$  minutes past 12pm that person 2 arrives.  $Y \sim \text{Unif}(0, 30)$

What is the probability that the first to arrive waits  $> 10$  mins for the other?

Compute:  $P(X + 10 < Y) + P(Y + 10 < X) = 2P(X + 10 < Y)$  (by symmetry)

1. What is “symmetry” here?
2. How do we integrate to compute this probability?

$$f_{X,Y}(x,y) = \left(\frac{1}{30}\right)^2$$
$$\iint_{\substack{x+10 < y \\ 0 \leq x, y \leq 30}} \left(\frac{1}{30}\right)^2 dx dy + \iint_{\substack{y+10 < x \\ 0 \leq x, y \leq 30}} \left(\frac{1}{30}\right)^2 dx dy$$



# The joy of meetings

Two people set up a meeting time. Each arrives independently at a time uniformly distributed between 12pm and 12:30pm.

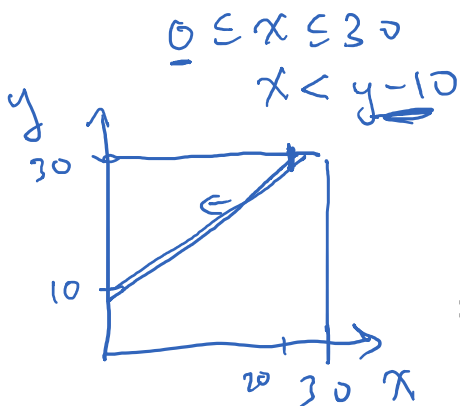
Define  $X = \#$  minutes past 12pm that person 1 arrives.  $X \sim \text{Unif}(0, 30)$

$Y = \#$  minutes past 12pm that person 2 arrives.  $Y \sim \text{Unif}(0, 30)$

What is the probability that the first to arrive waits  $>10$  mins for the other?

Compute:  $P(X + 10 < Y) + P(Y + 10 < X) = 2P(X + 10 < Y)$  (by symmetry)

$$= 2 \cdot \iint_{x+10 < y} f_{X,Y}(x,y) dx dy = 2 \cdot \iint_{\substack{x+10 < y, \\ 0 \leq x,y \leq 30}} (1/30)^2 dx dy \quad (\text{independence})$$



$$= \frac{2}{30^2} \int_{10}^{30} \int_0^{y-10} dx dy = \frac{2}{30^2} \int_{10}^{30} (y - 10) dy = \dots = \frac{4}{9}$$



Su | M | Tu | W | Th | F | Sa

# Interlude for jokes/announcements

# Announcements

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Mid-quarter feedback form

[link](#)

Open until: this Friday

Problem Set 4

Due: Monday 5/18 10am

Covers: Up to and including ~~today~~

Friday

# Announcements: CS109 contest

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Do something cool and creative  
with probability

Replaces one “passing” work requirement

Optional Proposal: Sat. 5/23 11:59pm  
Due: Monday 6/8, 11:59pm

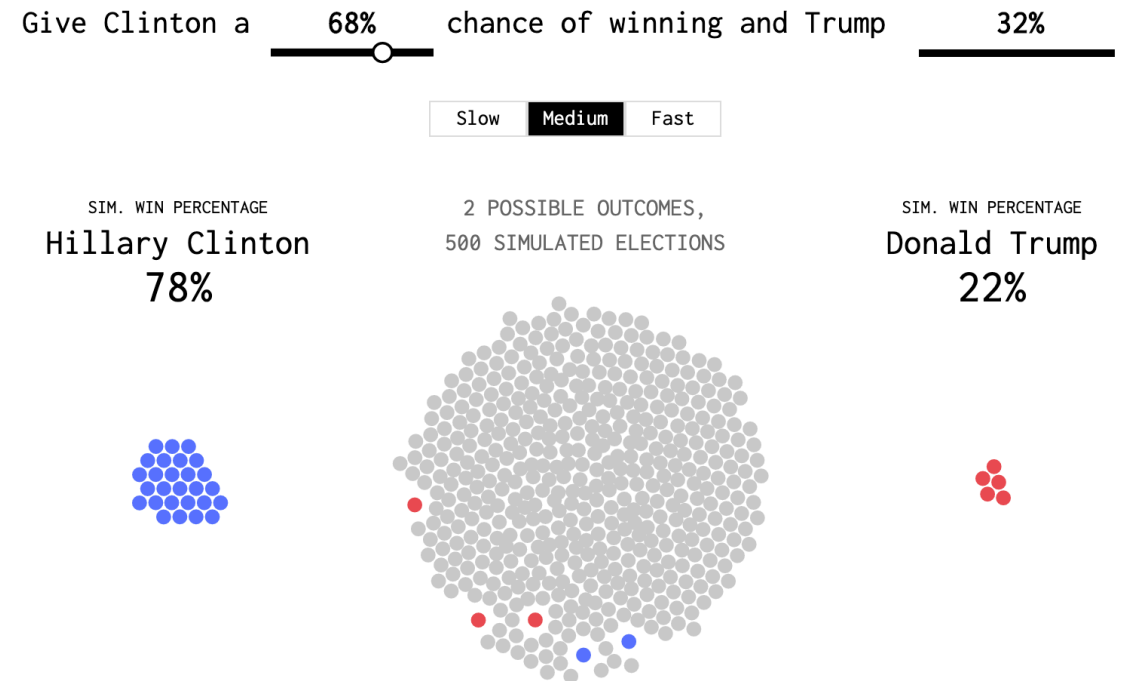
[https://web.stanford.edu/class/cs109/psets/cs109\\_contest.pdf](https://web.stanford.edu/class/cs109/psets/cs109_contest.pdf)

# Interesting probability news

## What That Election Probability Means

Even when you shift the probability far left or far right, the opposing candidate still gets some wins. That doesn't mean a forecast was wrong. That's just randomness and uncertainty at play. **The probability estimates the percentage of times you get an outcome if you were to do something multiple times.**

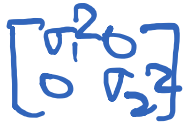
<https://flowingdata.com/2016/07/28/what-that-election-probability-means/>



[CS109 Current Events Spreadsheet](#)

The bivariate normal distribution of  $\mathbf{X} = (X_1, X_2)$ :

$$\mathbf{X} \sim \mathcal{N}(\boldsymbol{\mu}, \boldsymbol{\Sigma})$$

- Mean vector  $\boldsymbol{\mu} = (\mu_1, \mu_2)$
- Covariance matrix:  $\boldsymbol{\Sigma} = \begin{bmatrix} \sigma_1^2 & \rho\sigma_1\sigma_2 \\ \rho\sigma_1\sigma_2 & \sigma_2^2 \end{bmatrix}$   $\text{Cov}(X_1, X_2) = \text{Cov}(X_2, X_1) = \rho\sigma_1\sigma_2$
- Marginal distributions:  $X_1 \sim \mathcal{N}(\mu_1, \sigma_1^2), X_2 \sim \mathcal{N}(\mu_2, \sigma_2^2)$  
- For bivariate normals in particular,  $\text{Cov}(X_1, X_2) = 0$  implies  $X_1, X_2$  **independent**.

We will focus on understanding the **shape** of a bivariate Normal RV.

# Breakout Rooms

Check out the question on the next slide (Slide 47). Post any clarifications here!

<https://us.edstem.org/courses/109/discussion/60584>

Breakout rooms: 3 min. Introduce yourself!



# (X, Y) Matching (all have $\mu = (0, 0)$ )

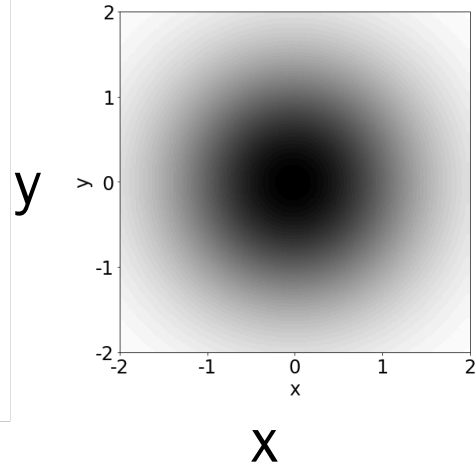
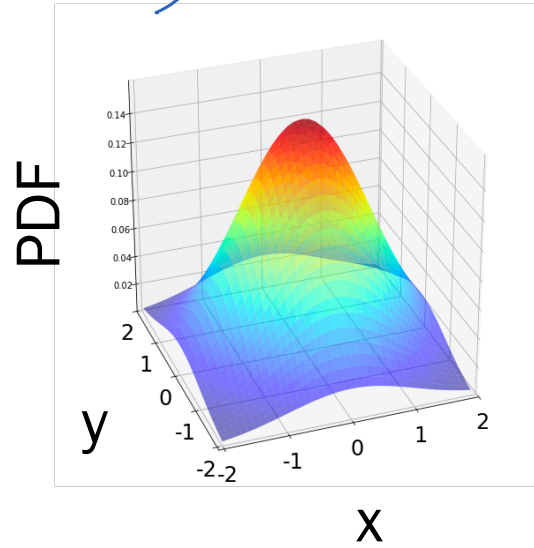


- A.  $\begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$     B.  $\begin{bmatrix} 1 & 0 \\ 0 & 2 \end{bmatrix}$   
 C.  $\begin{bmatrix} 1 & 0.5 \\ 0.5 & 1 \end{bmatrix}$     D.  $\begin{bmatrix} 1 & -0.5 \\ -0.5 & 1 \end{bmatrix}$

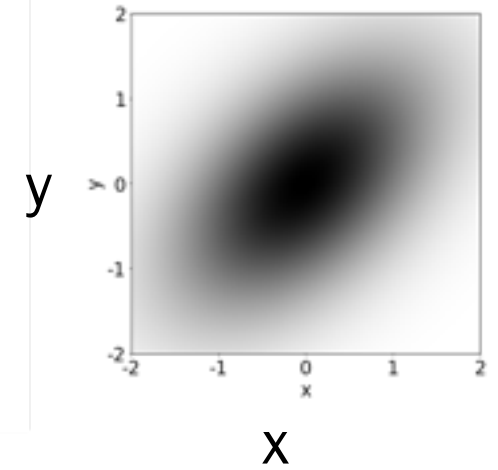
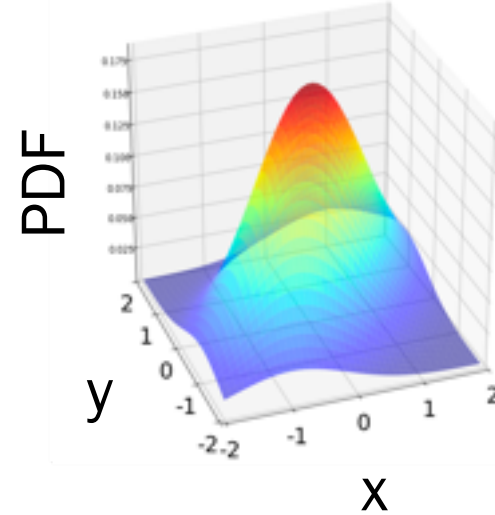
1.

3-D view

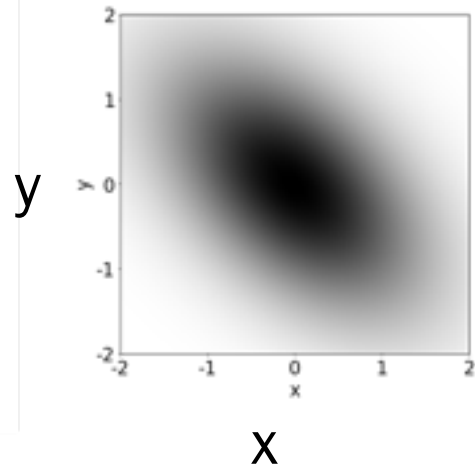
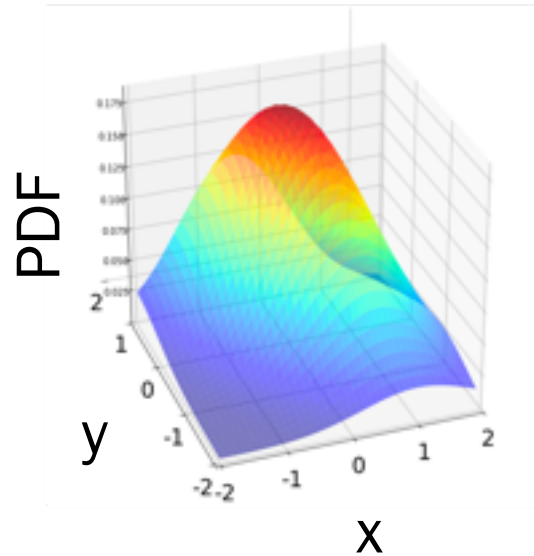
top-down view



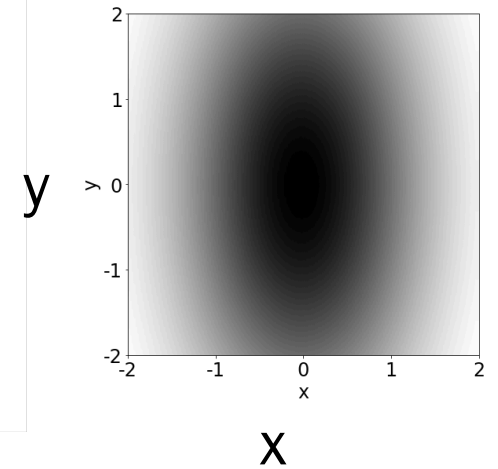
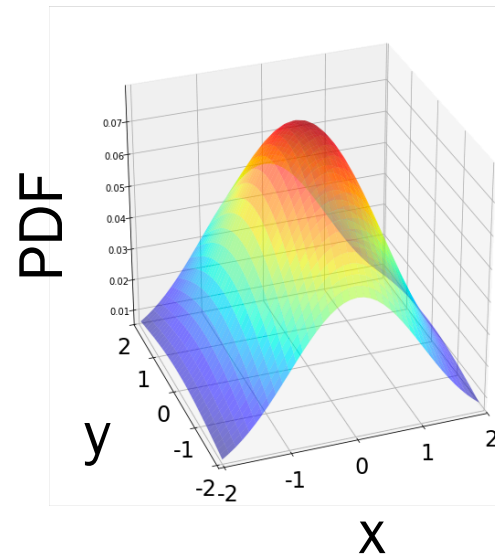
2.



3.



4.



# (X, Y) Matching (all have $\mu = (0, 0)$ )

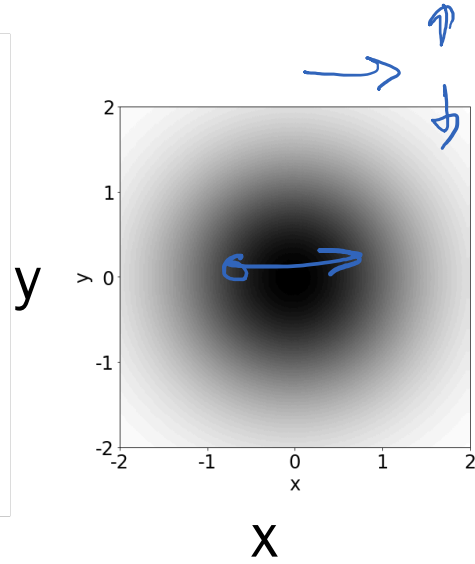
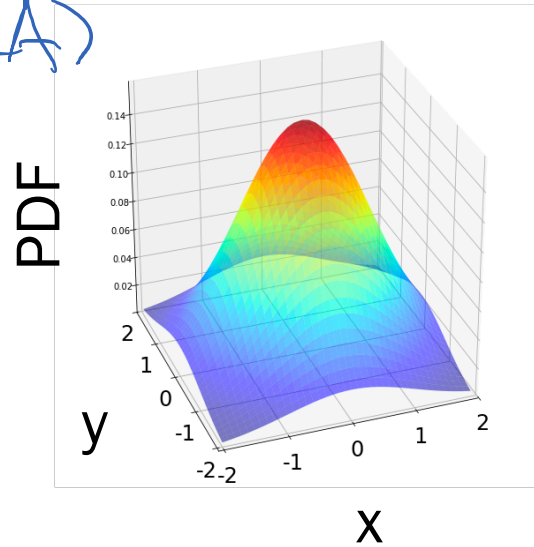
A.  $\begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$

B.  $\begin{bmatrix} 1 & 0 \\ 0 & 2 \end{bmatrix}$

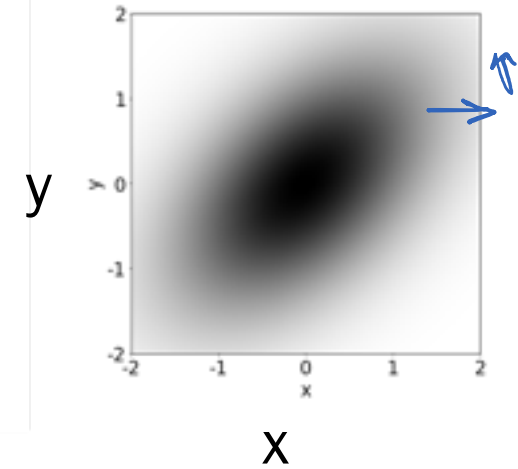
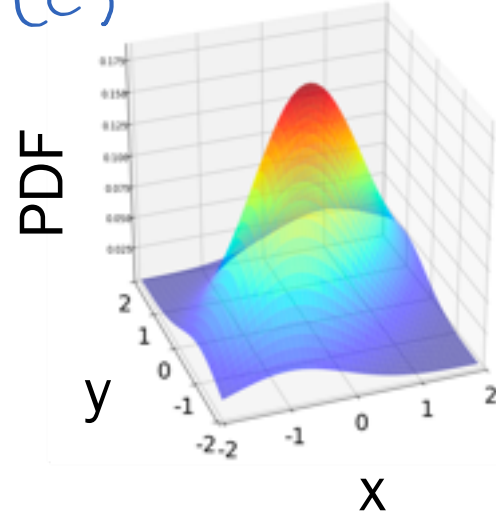
C.  $\begin{bmatrix} 1 & 0.5 \\ 0.5 & 1 \end{bmatrix}$

D.  $\begin{bmatrix} 1 & -0.5 \\ -0.5 & 1 \end{bmatrix}$

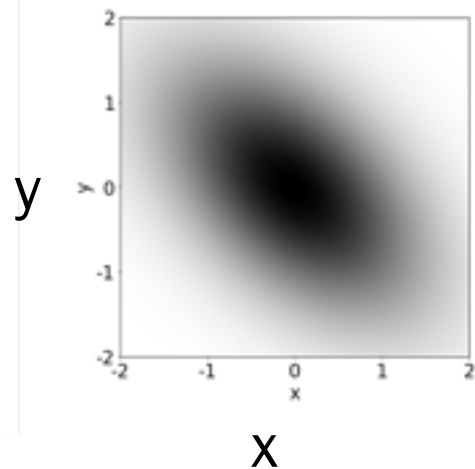
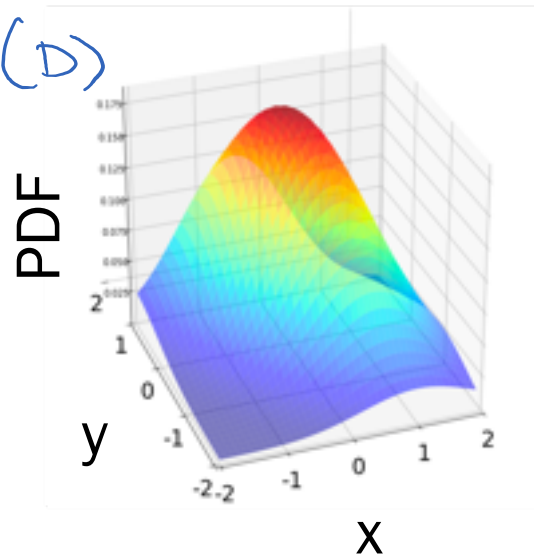
1. (A)



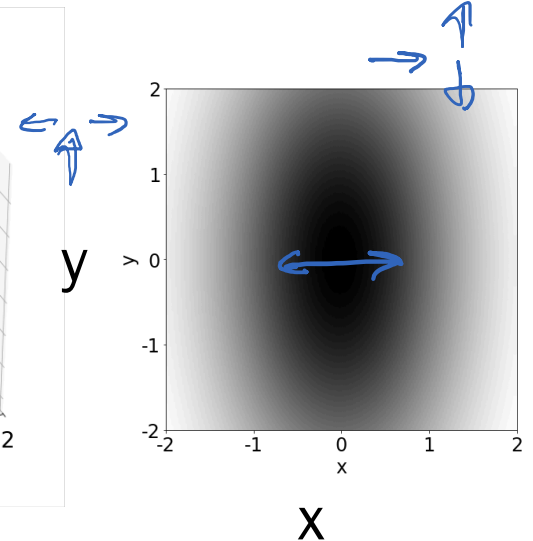
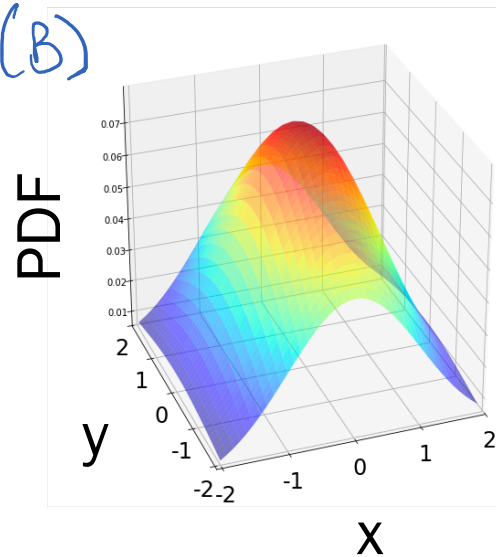
2. (C)



3. (D)



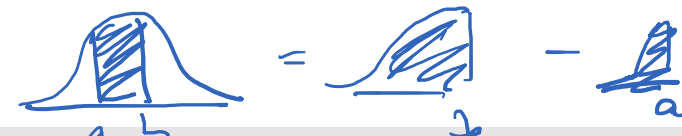
4. (B)





# Probabilities from joint CDFs

Recall for a single RV  $X$  with CDF  $F_X$ :



CDF:  $P(X \leq x) = F_X(x)$

$$P(a < X \leq b) = F_X(b) - F(a)$$

For two RVs  $X$  and  $Y$  with joint CDF  $F_{X,Y}$ :

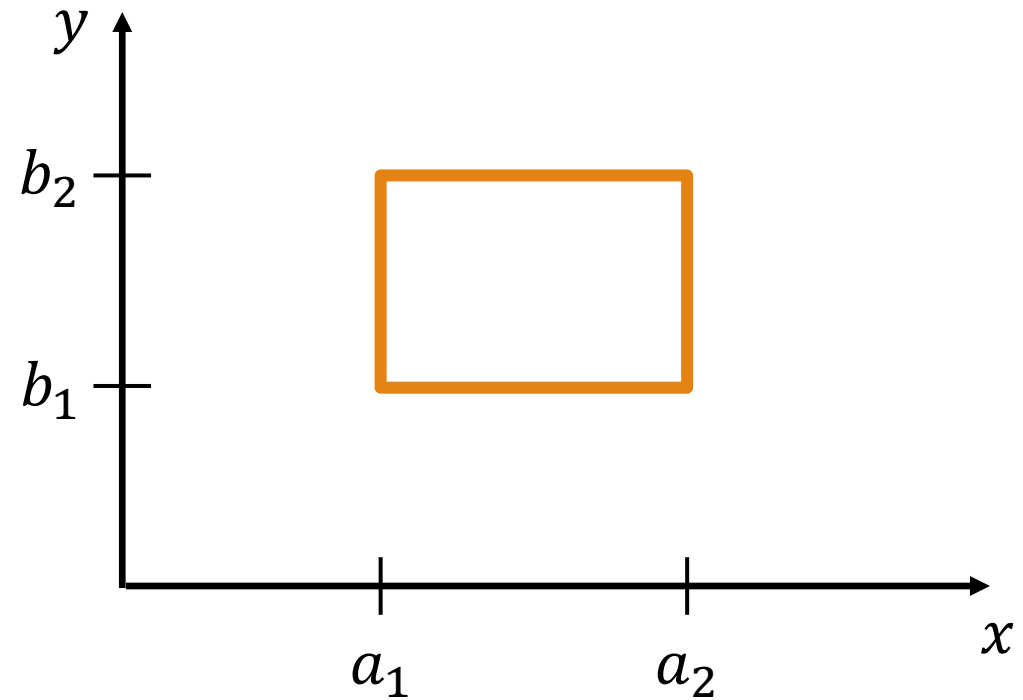
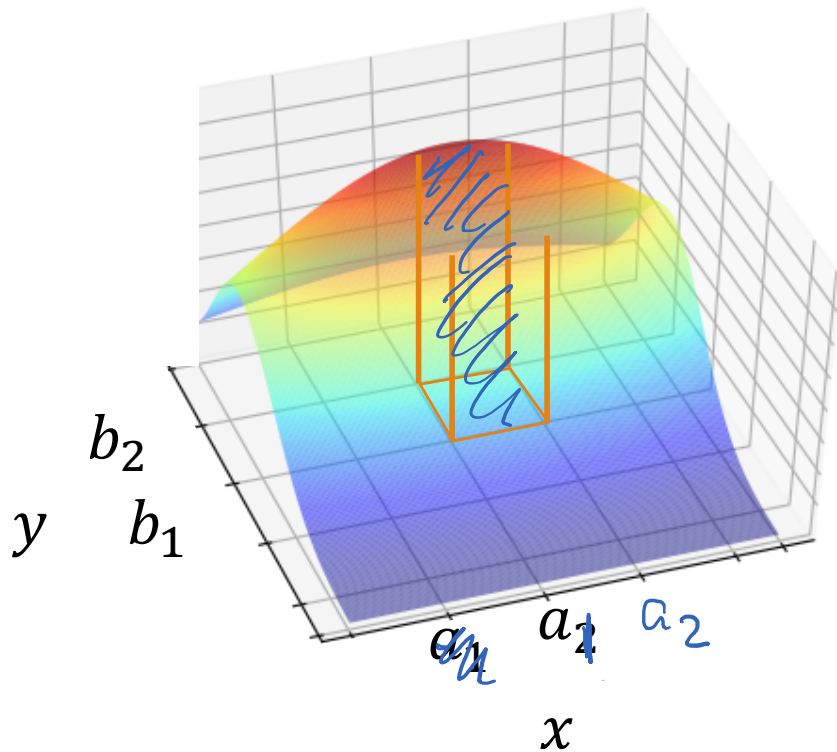
Joint CDF:  $P(X \leq x, Y \leq y) = F_{X,Y}(x, y)$

$$P(a_1 < X \leq a_2, b_1 < Y \leq b_2) = F_{X,Y}(a_2, b_2) - F_{X,Y}(a_1, b_2) - F_{X,Y}(a_2, b_1) + F_{X,Y}(a_1, b_1)$$

Note strict inequalities; these properties hold for both discrete and continuous RVs.

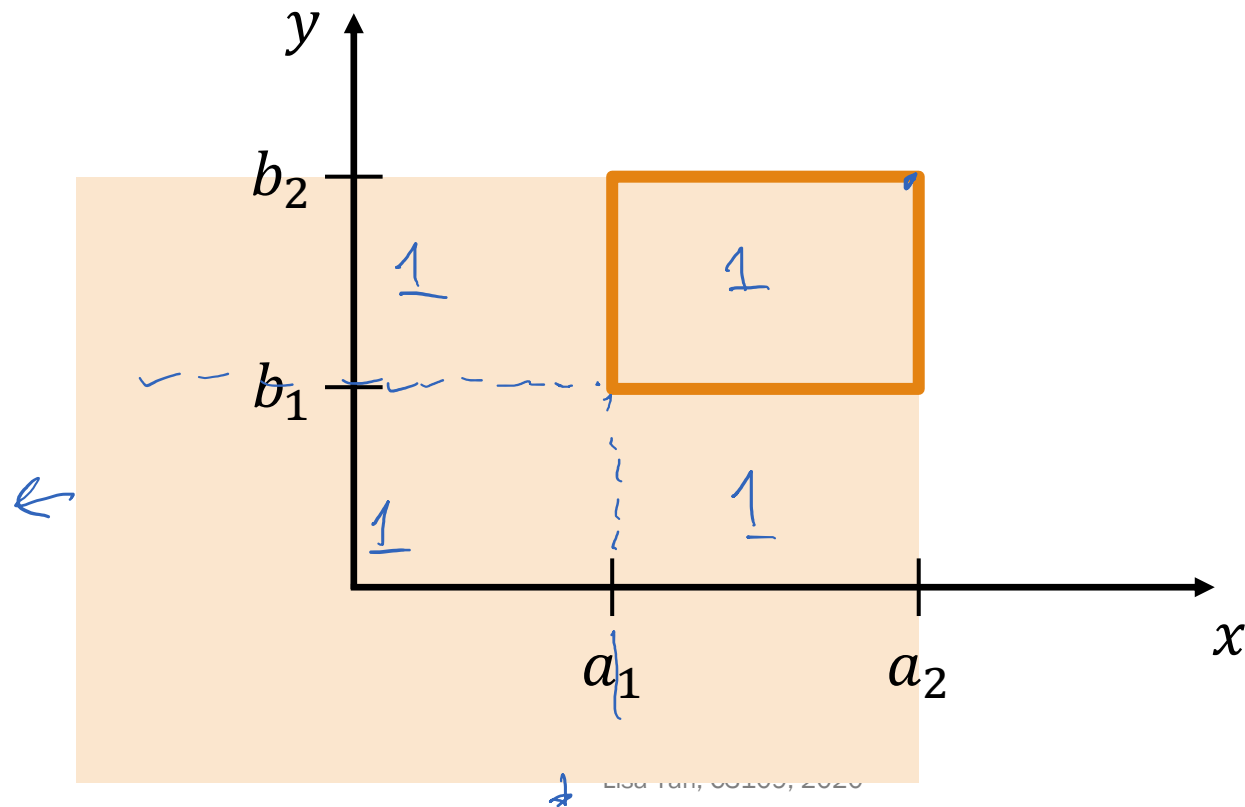
# Probabilities from joint CDFs

$$P(a_1 < X \leq a_2, b_1 < Y \leq b_2) = F_{X,Y}(a_2, b_2) - F_{X,Y}(a_1, b_2) - F_{X,Y}(a_2, b_1) + F_{X,Y}(a_1, b_1)$$



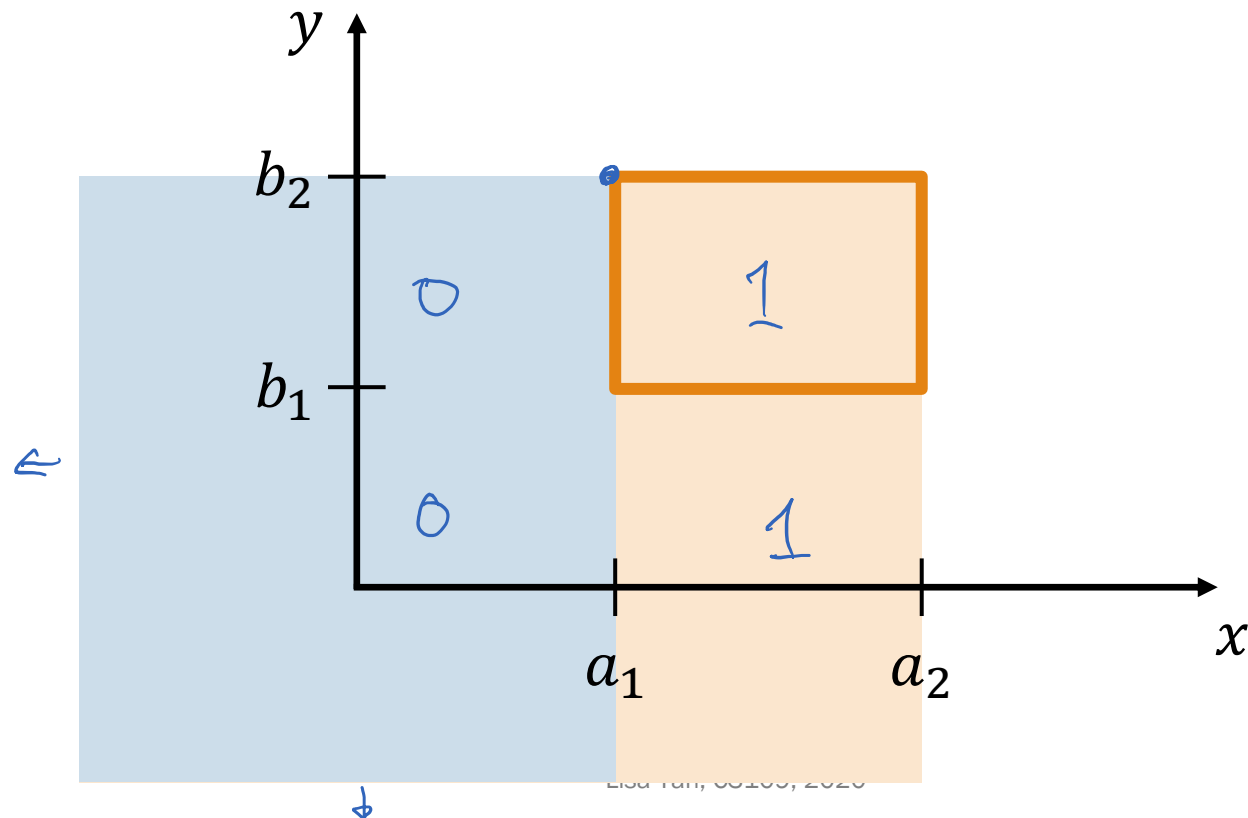
# Probabilities from joint CDFs

$$P(a_1 < X \leq a_2, b_1 < Y \leq b_2) = F_{X,Y}(a_2, b_2) - F_{X,Y}(a_1, b_2) - F_{X,Y}(a_2, b_1) + F_{X,Y}(a_1, b_1)$$



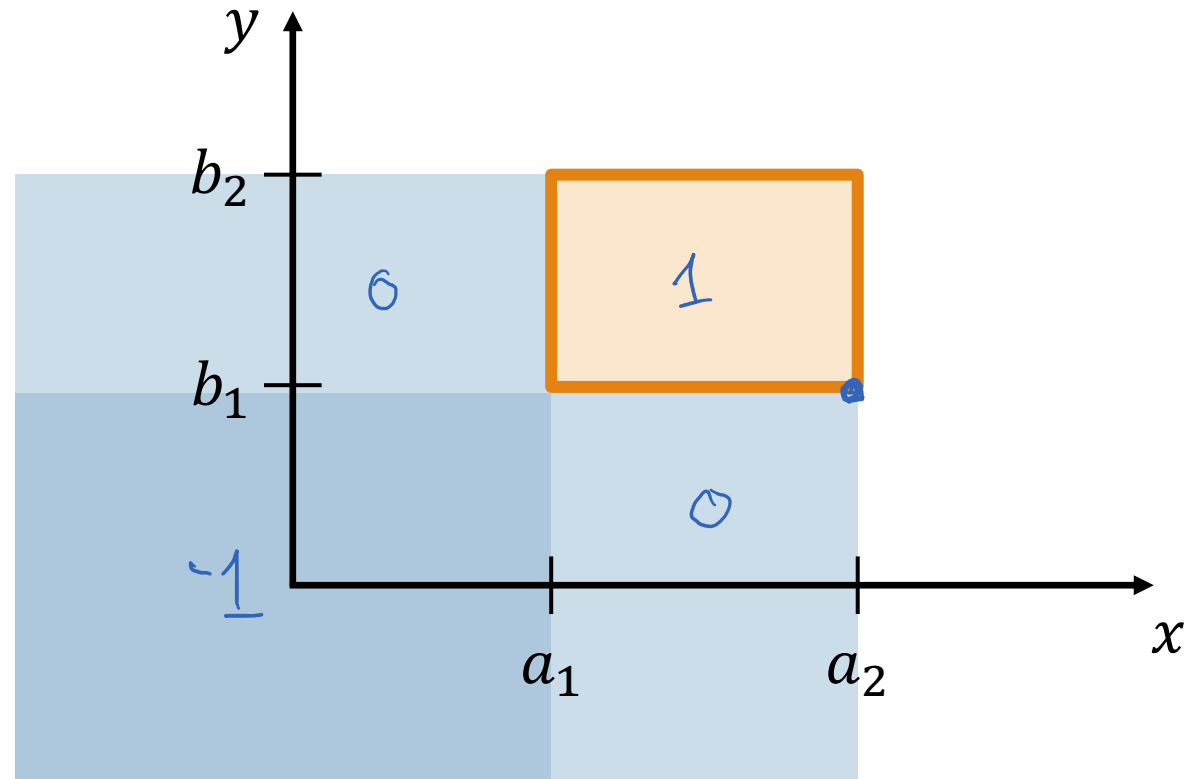
# Probabilities from joint CDFs

$$P(a_1 < X \leq a_2, b_1 < Y \leq b_2) = F_{X,Y}(a_2, b_2) - F_{X,Y}(a_1, b_2) - F_{X,Y}(a_2, b_1) + F_{X,Y}(a_1, b_1)$$



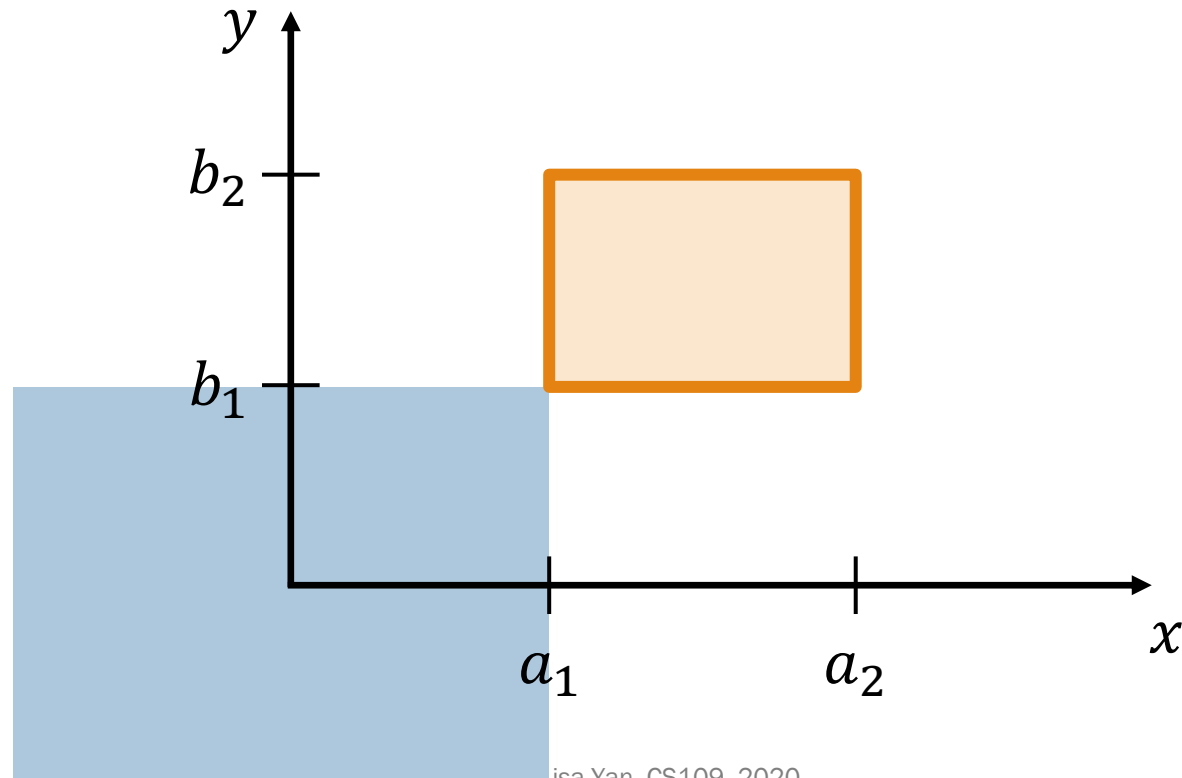
# Probabilities from joint CDFs

$$P(a_1 < X \leq a_2, b_1 < Y \leq b_2) = F_{X,Y}(a_2, b_2) - F_{X,Y}(a_1, b_2) - F_{X,Y}(a_2, b_1) + F_{X,Y}(a_1, b_1)$$



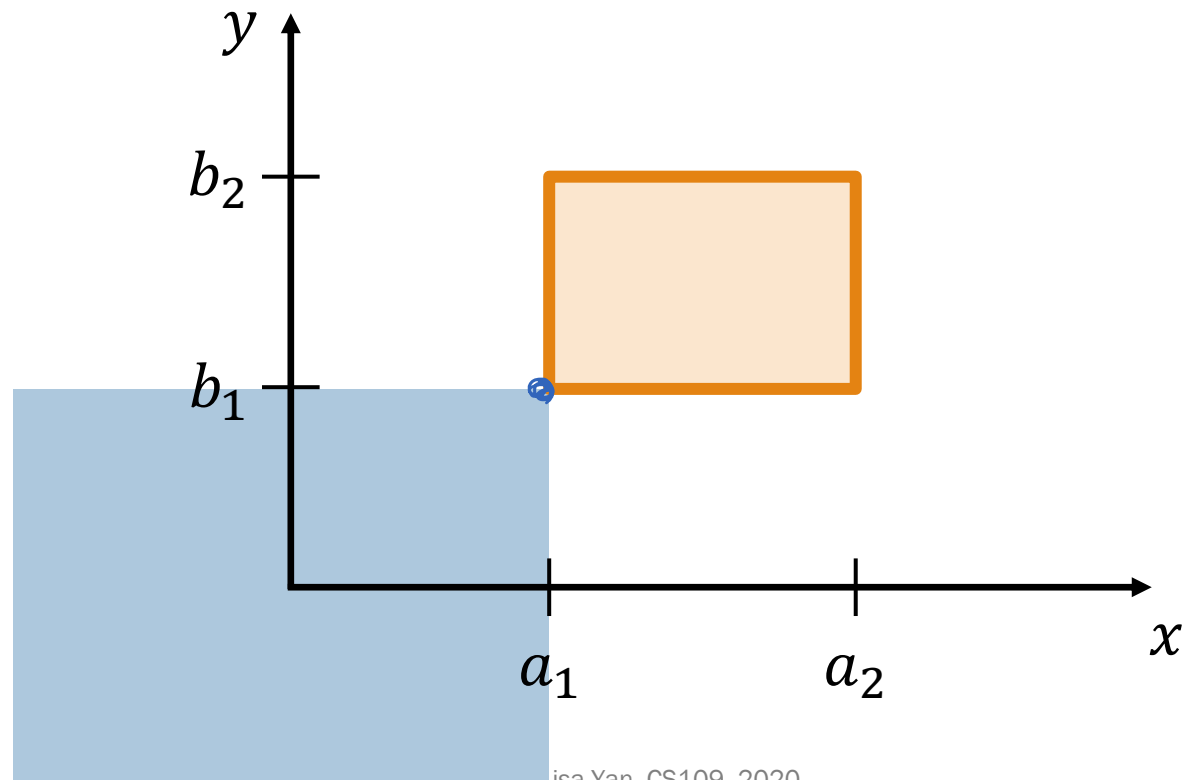
# Probabilities from joint CDFs

$$P(a_1 < X \leq a_2, b_1 < Y \leq b_2) = F_{X,Y}(a_2, b_2) - F_{X,Y}(a_1, b_2) - F_{X,Y}(a_2, b_1) + F_{X,Y}(a_1, b_1)$$



# Probabilities from joint CDFs

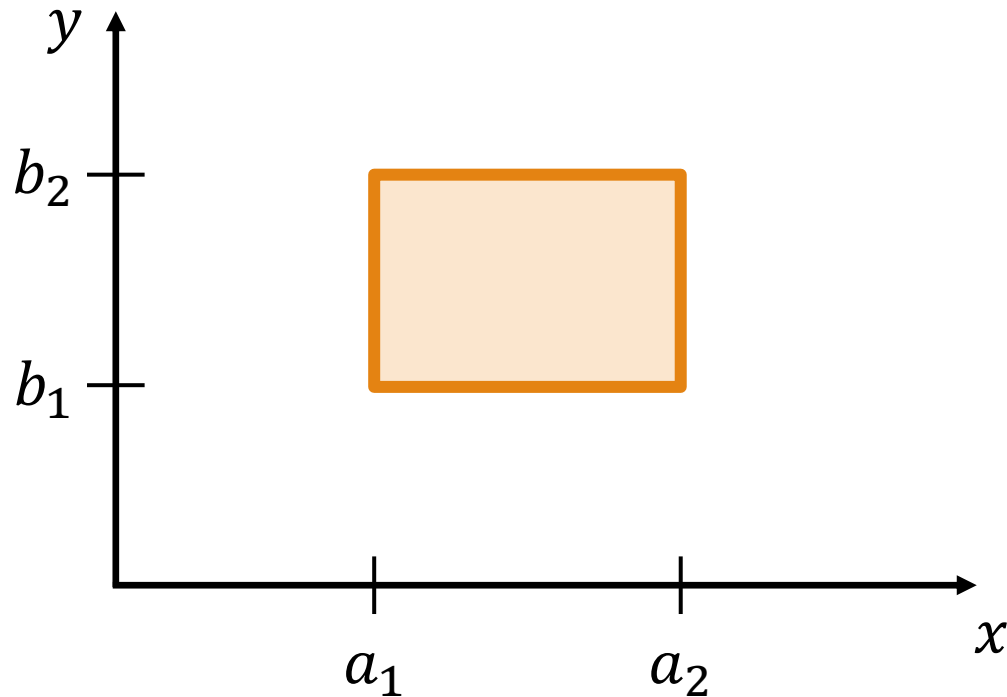
$$P(a_1 < X \leq a_2, b_1 < Y \leq b_2) = F_{X,Y}(a_2, b_2) - F_{X,Y}(a_1, b_2) - F_{X,Y}(a_2, b_1) + F_{X,Y}(a_1, b_1)$$



# Probabilities from joint CDFs

---

$$P(a_1 < X \leq a_2, b_1 < Y \leq b_2) = F_{X,Y}(a_2, b_2) - F_{X,Y}(a_1, b_2) - F_{X,Y}(a_2, b_1) + F_{X,Y}(a_1, b_1)$$





# Probability with Instagram!

$$P(a_1 < X \leq a_2, b_1 < Y \leq b_2) = F_{X,Y}(a_2, b_2) - F_{X,Y}(a_1, b_2) - F_{X,Y}(a_2, b_1) + F_{X,Y}(a_1, b_1)$$

(for next time)



In image processing, a Gaussian blur is the result of blurring an image by a Gaussian function. It is a widely used effect in graphics software, typically to reduce image noise.



# Gaussian blur (for next time)

$$P(a_1 < X \leq a_2, b_1 < Y \leq b_2) = F_{X,Y}(a_2, b_2) - F_{X,Y}(a_1, b_2) - F_{X,Y}(a_2, b_1) + F_{X,Y}(a_1, b_1)$$

In a Gaussian blur, for every pixel:

- Weight each pixel by the probability that  $X$  and  $Y$  are both within the pixel bounds
- The weighting function is a Bivariate Gaussian (Normal) standard deviation parameter  $\sigma$

Gaussian blurring with  $\sigma = 3$ :

$$f_{X,Y}(x, y) = \frac{1}{2\pi \cdot 3^2} e^{-(x^2 + y^2)/2 \cdot 3^2}$$

What is the weight of the center pixel?

$$P(-0.5 < X \leq 0.5, -0.5 < Y \leq 0.5) =$$

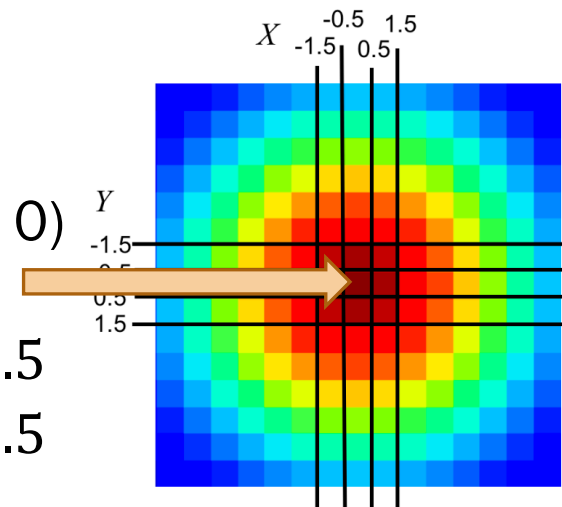
Weight matrix:

Center pixel: (0, 0)

Pixel bounds:

$$-0.5 < x \leq 0.5$$

$$-0.5 < y \leq 0.5$$



→ Independent  $X \sim \mathcal{N}(0, 3^2), Y \sim \mathcal{N}(0, 3^2)$

→ Joint CDF:  $F_{X,Y}(x, y) = \Phi\left(\frac{x}{3}\right) \Phi\left(\frac{y}{3}\right)$

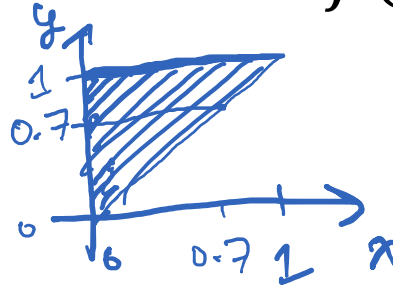
$$= 0.206$$

# Extra

# 1. Integral practice

Let  $X$  and  $Y$  be two continuous random variables with joint PDF:

$$f(x, y) = \begin{cases} 4xy & 0 \leq x, y \leq 1 \\ 0 & \text{otherwise} \end{cases}$$



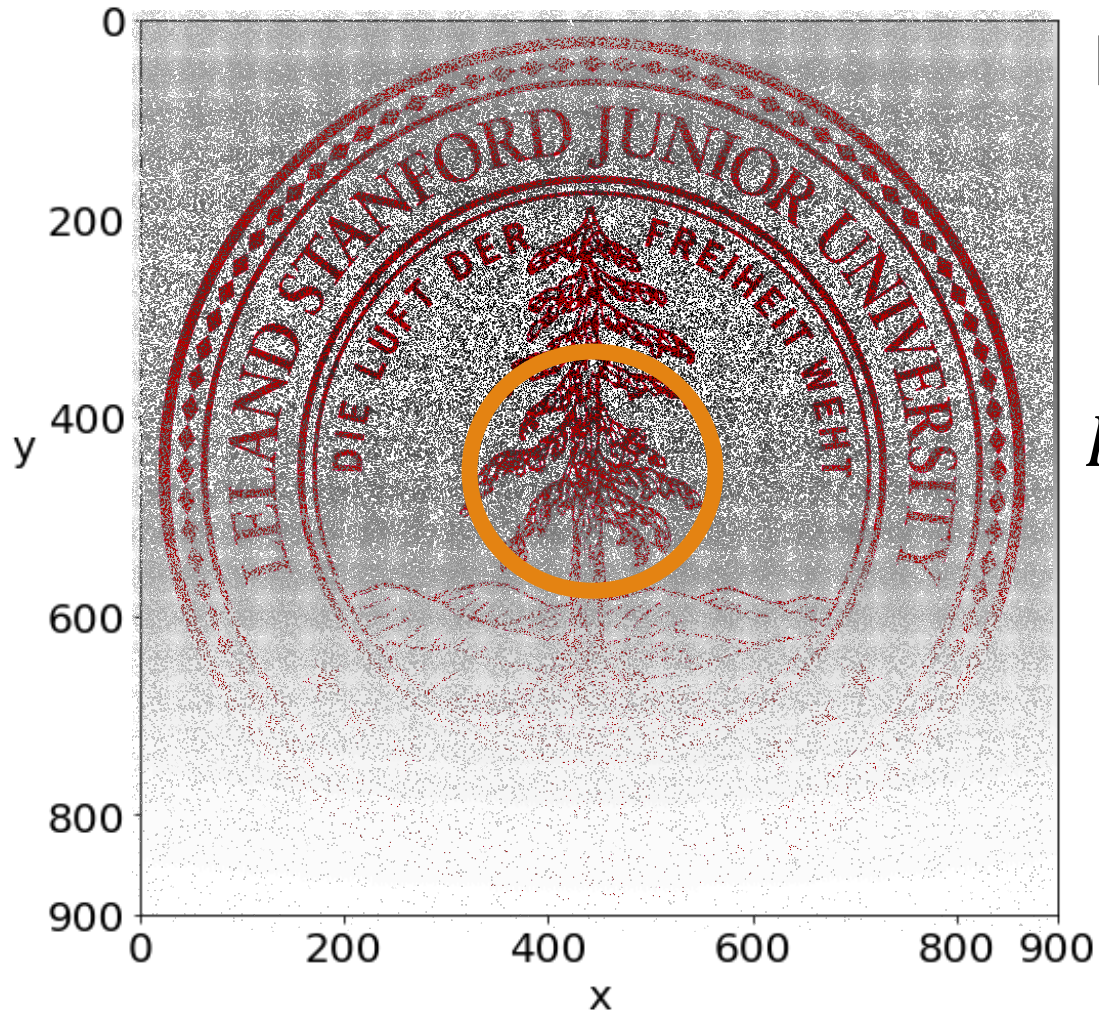
What is  $P(X \leq Y)$ ?

$$P(X \leq Y) = \iint_{\substack{x \leq y, \\ 0 \leq x, y \leq 1}} 4xy \, dx \, dy = \int_{y=0}^1 \int_{x=0}^y 4xy \, dx \, dy = \int_{y=0}^1 \int_{x=0}^y 4xy \, dx \, dy$$

$$= \int_{y=0}^1 4y \left[ \frac{x^2}{2} \right]_0^y \, dy = \int_{y=0}^1 2y^3 \, dy = \left[ \frac{2}{4} y^4 \right]_0^1 = \frac{1}{2}$$

$$\begin{aligned} P(X \leq Y) + P(X > Y) &= 1 \\ P(X \leq Y) + P(X \geq Y) &= 1 \end{aligned} \rightarrow 2P(X \leq Y) = 1 \rightarrow P(X \leq Y) = 1/2$$

## 2. How do you integrate over a circle?



P(dart hits within  $r = 10$  pixels of center)?

$$P(X^2 + Y^2 \leq 10^2) = \int \int_{x^2 + y^2 \leq 10^2} f_{X,Y}(x, y) dy dx$$

Let's try an example that doesn't involve integrating a Normal RV

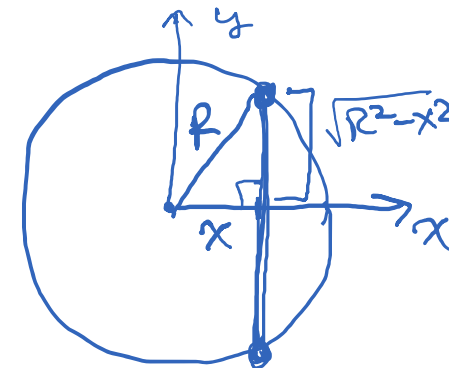


## 2. Imperfection on Disk

You have a disk surface, a circle of radius  $R$ . Suppose you have a single point imperfection uniformly distributed on the disk.

What are the marginal distributions of  $X$  and  $Y$ ? Are  $X$  and  $Y$  independent?

$$f_{X,Y}(x, y) = \begin{cases} \frac{1}{\pi R^2} & x^2 + y^2 \leq R^2 \\ 0 & \text{otherwise} \end{cases}$$



$$f_X(x) = \int_{-\infty}^{\infty} f_{X,Y}(x, y) dy = \frac{1}{\pi R^2} \int_{x^2 + y^2 \leq R^2} dy \quad \text{where } -R \leq x \leq R$$

$$= \frac{1}{\pi R^2} \int_{y=-\sqrt{R^2-x^2}}^{\sqrt{R^2-x^2}} dy = \frac{2\sqrt{R^2-x^2}}{\pi R^2}$$

$$f_Y(y) = \frac{2\sqrt{R^2-y^2}}{\pi R^2} \quad \text{where } -R \leq y \leq R, \text{ by symmetry}$$

*Handwritten note:*  $f(x) = \frac{1}{\pi R^2} \int_{x^2+y^2 \leq R^2} dx$

No,  $X$  and  $Y$  are **dependent**.  
 $f_{X,Y}(x, y) \neq f_X(x)f_Y(y)$